A Primer on Synthesizing Individual Participant Data Obtained From Complex Sampling Surveys: A Two-Stage IPD Meta-Analysis Approach

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Abstract

The increasing availability of individual participant data (IPD) in the social sciences offers new possibilities to synthesize research evidence across primary studies. Two-stage IPD meta-analysis represents a framework that can utilize these possibilities. While most of the methodological research on two-stage IPD meta-analysis focused on its performance compared with other approaches, dealing with the complexities of the primary and the meta-analytic data has received little attention, particularly when IPD are drawn from complex sampling surveys. Complex sampling surveys often feature clustering, stratification, and multi-stage sampling to obtain nationally or internationally representative data from a target population. Furthermore, IPD from these studies is likely to provide more than one effect size. To address these complexities, we propose a two-stage meta-analytic approach that generates model-based effect sizes in stage 1 and synthesizes them in stage 2. We present a sequence of steps, illustrate their implementation, and discuss the methodological decisions and options within. Given its flexibility to deal with the complex nature of the primary and meta-analytic data and its ability to combine multiple IPD sets or IPD with aggregated data, the proposed two-stage approach opens up new analytic possibilities for synthesizing knowledge from complex sampling surveys.

Keywords: Complex sampling survey, Individual participant data meta-analysis, Integrative data analysis, Multilevel meta-analysis, Multilevel structural equation modeling

A Primer on Synthesizing Individual Participant Data Obtained From Complex Sampling Surveys: A Two-Stage IPD Meta-Analysis Approach

Meta-analyses help create a cumulative body of knowledge in the social sciences.

Aggregate data (AD) and individual participant data (IPD) meta-analyses are two frameworks for synthesizing research results from multiple studies (Cooper & Patall, 2009). An AD meta-analysis synthesizes summary statistics from primary studies to draw conclusions based on the combined information (Borenstein et al., 2021). This approach is ideal for synthesizing research findings when the original data used in prior analyses are not accessible. However, the increasing availability of individual participant data shared by researchers and larger institutions offers new ways to synthesize research results from multiple studies via IPD meta-analysis. An IPD meta-analysis involves obtaining and synthesizing raw individual-level data from several studies (Riley et al., 2010). The simultaneous analysis and synthesis of IPD offer several advantages over single-study analysis and AD meta-analysis (Cooper & Patall, 2009; Curran & Hussong, 2009; Hussong et al., 2013; Wilcox & Wang, 2021). For instance, accessing raw participant data rather than summary data allows for testing relevant research questions while increasing statistical power to detect individual-level interactions and modeling the sources of within- and between-study variance. Furthermore, IPD meta-analysis represents a tool for evaluating replication in multi-lab studies (van Aert, 2020).

Combining raw participant data from several studies yields larger sample sizes than typical single-study designs. However, the between-study heterogeneity associated with the differences in sampling designs and measurements across studies may threaten the internal validity of an IPD meta-analysis (Hussong et al., 2013). For example, some studies may use probability sampling in which all members of a defined population have some known probability

of being selected for the sample, while others may use non-probability sampling in which the population members have an unknown probability of being selected. Pooled IPD data sets are likely to fall somewhere in between these two extremes.

Several procedures have been presented to synthesize IPD from non-probability samples (Curran & Hussong, 2009; Hofer & Piccinin, 2009; Wilcox & Wang, 2021). However, the procedures are unclear on how to synthesize IPD from so-called complex sampling surveys with different designs of single- or multi-stage probability sampling and hierarchical data structures (Hussong et al., 2013). National surveys – such as the National Assessment of Educational Progress (NAEP), German Socioeconomic Panel Study (SEOP), and National Educational Longitudinal Studies (NELS) – may include clustering, stratification, disproportionate sampling, and multiple stages of sample-selection (Hahs-Vaughn et al., 2011; Thomas & Heck, 2001). Similarly, multiple international surveys—such as the Trends in International Mathematics and Science Study (TIMSS), Program for International Student Assessment (PISA), and Teaching and Learning International Survey (TALIS)—also use complex sampling designs (Martin et al., 2016; OECD, 2017). These designs create analytic complexities for IPD meta-analysis and the integration of research evidence from multiple complex surveys.

In this tutorial, we propose a two-stage IPD meta-analytic approach to address these complexities and, ultimately, synthesize effect sizes from complex survey data. Our approach comprises an analysis of the IPD from complex sampling surveys (Stage 1) and a meta-analysis of the resultant effect sizes and sampling variances (Stage 2), both of which need to account for the data complexities. A recently proposed two-stage approach integrates IPD from single educational surveys with complex sampling designs and assumes that three-level meta-analysis with hierarchical effects accounts for the complexities of the meta-analytic data (Brunner et al.,

2022). The two-stage IPD approach presented in our paper extends these limitations by providing a more flexible approach that (a) utilizes advanced multivariate analyses to generate model-based effect sizes, for instance, via multilevel structural equation modeling (see Cheung & Jak, 2016); and (b) offers flexible representations of the stage-2 data via multilevel and multivariate meta-analysis with hierarchical, correlated, cross-classified, and subgroup structures. Researchers may use this approach to handle complex sampling (e.g., multilevel data), normal and non-normal data, categorical data, and missing data analysis into a unified, model-based framework on stage 1 (e.g., Muthén & Muthén, 2017; Skrondal & Rabe-Hesketh, 2004); and to integrate IPD from single and multiple surveys with IPD and IPD next to AD in stage 2. We illustrate the two-stage IPD meta-analysis with two examples and present a sequence of hands-on steps and a methodological toolbox (see Table 1).

Meta-Analysis of Individual Participant Data

IPD Meta-Analysis as an Approach to Cumulative Science

IPD meta-analysis is a methodological framework for analyzing and synthesizing individual participant data from two or more studies. An IPD meta-analysis involves collecting, validating, and re-analyzing raw data from individual studies to obtain combined results (Cooper & Patall, 2009). The approach is also known as coordinated analysis (Hofer & Piccinin, 2009), mega-analysis (Eisenhauer, 2021), and integrative data analysis (Curran & Hussong, 2009).

The relative advantage of IPD meta-analysis over other approaches stems from the level of data pooling. Access to individual participant data, rather than summary data, provides the opportunity to standardize analyses across studies, directly derive the effect sizes of interest, and increase the power to assess interactions between outcomes and participant characteristics (Cooper & Patall, 2009; Eisenhauer, 2021; Tierney et al., 2015). For example, IPD meta-analysis

can include subject- and study-level variables to compare different treatment effects on an outcome of interest. Thus, the analysis and synthesis of IPD from several studies is a cost-effective and robust methodology that preserves more detailed information than an AD meta-analysis (Debray et al., 2015).

The ongoing shift in the scientific community towards adopting open science practices positions IPD meta-analysis as a fundamental approach to help create a cumulative body of knowledge. The available data can address fundamental research questions in the psychological sciences and strengthen confidence in these results, including their robustness and generalizability. However, few published reports analyze data collected by other researchers (Kaufmann et al., 2016; Pigott et al., 2012). The slow adoption of IPD meta-analysis may be related to the challenges that psychologists face in pooling study effects across studies that are highly heterogeneous in their methodology (Curran & Hussong, 2009). Under ideal conditions (e.g., the same measures used across data sets), an IPD meta-analysis allows for testing and establishing the comparability of measures across studies, analytic levels, subgroups within samples, or study designs.

The Potential of IPD Meta-Analysis

The synthesis and analysis of raw participant data offer several advantages over single-study analysis. First, unlike single-study analysis, an IPD meta-analysis can directly test the replicability of a study effect across independent studies, as well as test the degree to which study and participant characteristics are related to variance in study effects (Debray et al., 2015). Thus, IPD meta-analysis can investigate the replicability of novel hypotheses not considered in a single-study analysis. Second, IPD meta-analysis extends the range of statistical methods that can answer relevant research questions while giving the analyst complete control over the

comparability of the analytic models. Pooling raw participant data from several studies also yields larger sample sizes than typical single-study designs. Such additional data can be used to estimate and synthesize complex statistical parameters, such as moderation and mediation effects, factor loadings, and model-derived parameters, for instance, reliability coefficients (Pigott et al., 2012; Scherer & Teo, 2020). Finally, pooling IPD from several samples broadens the external validity of an IPD meta-analysis. Between-study heterogeneity due to sampling can be directly accounted in an IPD meta-analysis, enabling researchers to test for potential differences across samples, include adjustments for these differences, and understand why such differences exist (Hussong et al., 2013).

IPD meta-analysis also offers advantages over AD-only meta-analysis. First, an AD meta-analysis risks drawing conclusions subject to aggregation bias (Kaufmann et al., 2016). Given that summary data are analyzed in AD meta-analysis, data on participant characteristics may be lost when there is non-normality in the data. In contrast, an IPD meta-analysis can use the raw participant data to perform within-study subgroup analyses that might not have been conducted in the original studies. The additional information in an IPD meta-analysis decreases the risk of ecological bias, increases statistical power to detect individual-level interactions, and disaggregates participant-level and study-level effects (Cooper & Patall, 2009). Second, whereas the quality of an AD meta-analysis depends on published results, an IPD meta-analysis has access to the raw data in the original studies. The additional information gives the analysts complete control over the comparability of analytic models. For example, they can test the comparability of measures across studies through measurement harmonization procedures (i.e., measurement invariance, linkage, and equating tests). Third, IPD meta-analysis can accommodate more complex statistical analyses that are not feasible when only study-level data

are available. The analysis of raw participant data enables researchers to standardize analyses across studies and directly derive effect sizes of interest (Cooper & Patall, 2009; Eisenhauer, 2021; Tierney et al., 2015). For example, multivariate approaches—such as multivariate analysis of variance (MANOVA), multiple regression (Becker & Wu, 2007), multilevel models (Lorah, 2018), and structural equation models (Cheung & Chan, 2005)—can be utilized for IPD meta-analysis.

Although IPD meta-analysis has several advantages over single-study analysis and AD meta-analysis (Cooper & Patall, 2009; C. T. Smith et al., 2016), an IPD meta-analysis is not always feasible. For example, an IPD meta-analysis may pool data sets from studies with divergent measures or measurement scales, which cannot be harmonized or standardized (Rogozińska et al., 2017). This measurement heterogeneity threatens the comparability of the respective effect sizes and ultimately the validity of the meta-analytic results. Data availability bias is another concern in IPD meta-analysis. Researchers may be able to retrieve more AD than IPD (Wicherts et al., 2006). The lack of access to primary-study data sets exposes IPD meta-analysis results to selection or availability bias (Ahmed et al., 2012). Thus, researchers may want to perform an AD meta-analysis in addition to or in combination with an IPD meta-analysis when raw data cannot be retrieved from all primary studies. If AD and IPD allow researchers to extract and generate the same type of effect sizes from sufficiently comparable measures and constructs, the combination between these two data sources can add great analytic and substantive value (Scherer et al., 2021). For instance, meta-analysts can explore the possible differences between small- and large-scale studies, sampling designs, or reporting practices (e.g., AD vs. IPD reporting). However, combining AD and IPD in one meta-analysis may not be reasonable if they largely differ in the pooled effect sizes and amounts of heterogeneity.

Analytic Approaches

Researchers can conduct an IPD meta-analysis by taking a one-stage or two-stage analytic approach. In the one-stage approach, individual participant data from different studies are modeled simultaneously while accounting for the clustering of participants within studies. However, one-stage IPD meta-analysis methods require commensurate measures across studies, and extensive work must be done when variables are on different scales. Alternatively, the two-stage approach analyzes individual participant data from each study independently, then combines standardized effect size estimates using meta-analytic models (Cooper & Patall, 2009; Smith et al., 2016). In the following section, we describe the one-stage and two-stage approaches.

One-stage IPD meta-analysis. In the one-stage approach, a single statistical model pools the IPD (see Burke et al., 2017; Debray et al., 2015; Wilcox & Wang, 2021). The pooling of IPD from several studies requires having measures from each study that reflect the same construct and having construct scores that are scaled proportionally across studies (Bauer & Hussong, 2009). Models of confirmatory factor analysis, item response theory, or moderated nonlinear factor analysis can be used to achieve this (see (Bauer & Hussong, 2009; Curran & Hussong, 2009; Hussong et al., 2013; Kush et al., 2022)). In situations in which studies share common items, the measurement models are first estimated in each study separately and then in all studies simultaneously (Curran & Hussong, 2009). Second, different invariance constraints are imposed and tested to identify invariant and non-invariant model parameters (e.g., equal factor loadings or item discriminations, equal intercepts or item difficulties). If a sufficiently large set of invariant parameters exists, then the scale scores can be meaningfully compared across studies (Bauer & Hussong, 2009).

An alternative and more common situation is one in which studies do not share common items or scales. In this situation, researchers can use pre-analysis approaches to compare results from multiple studies that do not share common scales. For example, the standardization of scores with a common metric (e.g., T scores based on between-person differences or a reference group), the use of proportion pass/fail items on instruments of different lengths, or the use of international diagnostic standards can help researchers harmonize measures across studies (Hofer & Piccinin, 2009). However, in such a scenario, researchers would not have evidence that the same construct is assessed in a psychometrically equivalent way across studies or samples.

Once commensurately scaled variables have been created, multilevel models can be used to account for the hierarchical structure of the dataset and quantify effect size heterogeneity in the one-stage approach. Typically, these models specify two analytic levels the participant and the study level—with random intercepts and slopes (Wilcox & Wang, 2021). These models can be extended even further by additional levels, particularly when the IPD already have a clustered data structure. For example, meta-analysts might be interested in synthesizing the contextual effect of a level-2 variable (Z_{jk}) on an outcome variable Y_{ijk} for individual participants i in clusters j and primary study k after controlling for a level-1 variable X_{ijk} . These clusters may represent classrooms, schools, neighborhoods, or companies. The average contextual effect (γ_{010}) and its variation ($\sigma_{v_{01}}^2$) across studies can be estimated via a three-level random-slopes model (with individual participants $i = 1, \dots, I$; clusters $j = 1, \dots, J$; primary studies $k = 1, \dots, K$; Declercq et al., 2020):

$$\text{Level 1 (individual participants):} \quad Y_{ijk} = \beta_{0jk} + \beta_{1jk}X_{ijk} + e_{ijk}$$

$$\text{Level 2 (clusters):} \quad \beta_{0jk} = \beta_{00k} + \beta_{01k}Z_{jk} + u_{0jk}$$

$$\beta_{1jk} = \beta_{10k} + u_{1jk}$$

$$\text{Level 3 (primary studies):} \quad \beta_{00k} = \gamma_{000} + v_{00k}$$

$$\beta_{01k} = \gamma_{010} + v_{01k}$$

$$\beta_{10k} = \gamma_{100} + v_{10k}$$

In this model specification, β_{0jk} and β_{1jk} are the cluster- and study-specific intercepts and slopes, X_{ijk} is the level-1 predictor, and e_{ijk} represents level-1 residuals with $e_{ijk} \sim N(0, \sigma_e^2)$.

Cluster- and study-specific intercepts β_{0jk} are explained further by contextual variable Z_{jk} , yielding the effect size of interest, that is, the study-specific contextual effect β_{01k} . The level-2 random effects are assumed to follow a multivariate normal distribution,

$$\begin{bmatrix} u_{0jk} \\ u_{1jk} \end{bmatrix} \sim MVN \left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_{u_0}^2 & \sigma_{u_0 u_1} \\ \sigma_{u_0 u_1} & \sigma_{u_1}^2 \end{bmatrix} \right), \text{ and are independent of the level-1 residuals. Besides the}$$

level-2 intercepts β_{00k} and the random slopes β_{10k} (i.e., the study-specific slopes of the effect of X_{ijk} on Y_{ijk}), the contextual effects β_{01k} are decomposed further into a fixed effect (γ_{010}) and study-specific deviations from it (v_{01k}). The level-3 random effects are assumed to follow a

$$\text{multivariate normal distribution, } \begin{bmatrix} v_{00k} \\ v_{01k} \\ v_{10k} \end{bmatrix} \sim MVN \left(\begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_{v_{00}}^2 & \sigma_{v_{00}v_{01}} & \sigma_{v_{00}v_{10}} \\ \sigma_{v_{00}v_{01}} & \sigma_{v_{01}}^2 & \sigma_{v_{01}v_{10}} \\ \sigma_{v_{00}v_{10}} & \sigma_{v_{01}v_{10}} & \sigma_{v_{10}}^2 \end{bmatrix} \right), \text{ and are}$$

independent of level-1 residuals and level-2 random effects. Notably, some assumptions in this model, such as the existence of the random slopes β_{1jk} and β_{10k} , might be modified, depending on the researchers' objectives and the nature of the data. Essentially, the model generates effect sizes of interest for each primary study (i.e., the contextual effects β_{01k}), pools them into an average effect size (γ_{010}), and quantifies their heterogeneity across primary studies ($\sigma_{v_{01}}^2$).

The multilevel models used in one-stage IPD meta-analysis offer several advantages over AD meta-analysis. First, they estimate variances within and between studies and additional clusters, and can include study-, cluster-, and participant-level predictors (Debray et al., 2015).

Second, maximum likelihood (ML) and restricted maximum likelihood estimation (REML) can be used to obtain precise fixed effects and within-study variance components (Wilcox & Wang, 2021). Finally, these multilevel analyses directly model the distribution of the IPD and can be specified with the flexible framework of generalized linear mixed models (Burke et al., 2017), including multilevel structural equation modeling.

Two-stage IPD meta-analysis. Two-stage IPD meta-analysis analyzes data from each study independently and then combines resultant effect size estimates using meta-analytic models. In the first stage, model-based effect sizes (θ_k) and their sampling variances (v_k) are estimated based on some analytic model. In our previous example, the effect size of interest was a contextual effect of a level-2 variable Z_{jk} . In the two-stage approach, a multilevel contextual model is fit to data sets for each primary study k separately, providing a set of K regression coefficients β_{01k} as effect sizes and their sampling variances v_k . The model generating these estimates can be specified as follows (with individual participants $i = 1, \dots, I$; clusters $j = 1, \dots, J$; primary studies $k = 1, \dots, K$):

$$\text{Level 1 (individual participants):} \quad Y_{ijk} = \beta_{0jk} + \beta_{1jk}X_{ijk} + e_{ijk}$$

$$\text{Level 2 (clusters):} \quad \beta_{0jk} = \beta_{00k} + \beta_{01k}Z_{jk} + u_{0jk}$$

$$\beta_{1jk} = \beta_{10k} + u_{1jk}$$

with the study-specific L1 residuals $e_{ijk} \sim N(0, \sigma_{e_k}^2)$ and level-2 random effects,

$$\begin{bmatrix} u_{0jk} \\ u_{1jk} \end{bmatrix} \sim MVN \left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_{u_{0k}}^2 & \sigma_{u_{0k}u_{1k}} \\ \sigma_{u_{0k}u_{1k}} & \sigma_{u_{1k}}^2 \end{bmatrix} \right). \text{ As in the one-stage approach, meta-analysts may or}$$

may not specify the random slope β_{1jk} at the level of clusters.

In the second stage, extracted effect sizes (β_{01k}) are combined meta-analytically via fixed- or random-effects models. In the random-effects model (REM), the observed effect sizes β_{01k} are decomposed into a true effect size θ_k and sampling error r_k :

$$\beta_{01k} = \theta_k + r_k \text{ with } r_k \sim N(0, \sigma_{r_k}^2).$$

The variances $\sigma_{r_k}^2$ are study-specific and considered to be known. In our example, the effect size θ_k is decomposed further as follows (van Aert, 2020):

$$\theta_k = \mu + u_k \text{ with } u_k \sim N(0, \sigma_u^2).$$

In the REM, μ is the average population effect size, u_k is the deviation of the study's true effect θ_k from the average population effect size μ , σ_u^2 is the between-study variance (often referred to as τ^2), r_k is the deviation of the study's observed effect from the study's true effect, and $\sigma_{r_k}^2$ is the sampling variance of the study k . The estimate of the average population effect size is a weighted average in the REM (Borenstein et al., 2021): $\hat{\mu} = (\sum_{k=1}^K \theta_k w_k) / (\sum_{k=1}^K w_k)$ with weights $w_k = 1/(v_k + \tau^2)$ and standard error $SE(\hat{\mu}) = 1/\sqrt{\sum_{k=1}^K w_k}$.

The one-stage and two-stage approaches can yield similar estimates of average effects. However, the two-stage IPD meta-analysis is recommended in meta-analyses where the IPD have several dependency levels (e.g., participants nested in classrooms and time points), and complex statistical models are estimated to derive effect sizes (e.g., multilevel structural equation models to estimate contextual or cross-level interaction effects; Declercq et al., 2020). For instance, in a data set with several analytic levels, estimation of one-stage IPD meta-analytic models is limited by the computational demands of model estimation, possible non-convergence, and unavailability of between-study variance in effect sizes derived from model parameters (e.g., indirect effects or contextual effects of cluster-aggregated variables). However, two-stage IPD meta-analysis circumvents and addresses these limitations (Declercq et al., 2020). Moreover, it

provides a flexible framework to examine measurement invariance and create commensurable measures when measurement models of scales are involved to generate effect sizes in stage 1. If commensurable measures cannot be created, meta-analysts can explore the extent to which between-study heterogeneity may be due to different scales or measurement models in stage 2.

Complex Survey Data

National and international surveys undertaken by governmental organizations and larger institutions, such as the Organization for Economic Cooperation and Development (OECD) or the United Nations, often incorporate complex sampling designs to obtain nationally representative data from a target population. These designs deviate from simple random sampling designs and typically include clustering, stratification, disproportionate sampling, and multiple stages of sample selection (Heeringa et al., 2017). These features are used in national surveys—such as the Longitudinal Surveys of Australian Youth (LSAY), National Educational Panel Study (NEPS), and National Educational Longitudinal Studies (NELS) (Stapleton & Kang, 2018)—as well as international surveys such as the Programme for the International Assessment of Adult Competencies (PIAAC), Progress in International Reading Literacy Study (PIRLS), and International Computer and Information Literacy Study (ICILS). Surveys with complex sampling designs can raise several statistical modeling challenges. For instance, multi-stage sampling designs create a clustered data structure with dependencies among data points (e.g., students nested in classrooms or participants nested in municipalities). Failing to address such clustered structures in the data analysis may elicit spurious statistical significance and, ultimately, ecological fallacies (Geldhof et al., 2014; Stapleton et al., 2016). Moreover, ignoring different selection probabilities at respective sampling stages places more importance on some participants or clusters based solely on sampling design (Rutkowski et al., 2010). Thus, meta-

analysts interested in working with complex survey data need to be aware of how the data are collected and account for complex sampling designs in the analysis and synthesis of IPD.

Clustered Data Structures

Complex surveys often follow a multi-stage sampling design to optimize costs and achieve operational feasibility (Rust, 2013). The cluster sampling procedure comprises two steps: During the first step, primary sampling units are selected from the population, and during the second step, participants from selected clusters are sampled. The cluster sampling compensates for the lack of a sampling frame from the target population and ensures that the sample has sufficient respondents to describe the populations of interest (Stapleton & Thomas, 2008). However, clustered data violate the assumption of independent residuals, as participants from a cluster tend to be more homogeneous than participants from different clusters. Such homogeneity can make estimation of parameters of interest and associated standard errors inefficient (Stapleton et al., 2016). Multilevel models, multi-group analyses, cluster-robust estimation methods, and fixed-effects models are key approaches to address clustered data structures (e.g., McNeish & Kelley, 2018; Snijders & Bosker, 2012).

Survey Weights

Survey weights are a central feature of complex sampling designs to ensure appropriate representation of target populations, correct for nonresponses when sampling clusters or participants do not provide data, or select individuals based on the principal cluster unit's sample size (Rust, 2013; Stapleton, 2013). Failing to account for disproportionate sampling can lead to underestimated standard errors, overestimated test statistics, and increased Type I error probabilities (Rutkowski & Rutkowski, 2016). However, to what extent these effects might be observed depends on how informative the survey weights are (Asparouhov, 2006).

Typically, survey weights represent the inverse of the selection probability of an individual or cluster. In cluster sampling designs, a weight can be separated into two components that reflect the inclusion probability of a cluster j and a participant i . The first part of the weight is the cluster-level weight, which is the inverse inclusion probability of the cluster p_j . The second component is participant weight, which is the inverse conditional inclusion probability $p_{i|j}$ of the individual i given that the cluster j has been selected in the sample. Notably, sampling weight types differ between complex surveys, and researchers always should review the weights' meaning, composition, and scaling when incorporating them into data analyses.

Stratified Samples

Stratification is used in complex surveys to improve the precision of estimates and allow for oversampling within specific subgroups of interest (Rust, 2013). For example, samples might be stratified to obtain equal numbers of urban and rural residents, larger numbers of minority group members, or equal numbers of men and women. Implicit or explicit stratification generally is used in complex sample surveys. While the former describes the sorting of the sample based on some characteristics (e.g., geographical area or ethnicity), the latter describes the breakdown of the sample using individual or group characteristics. In stratifying a sample, the allocated sample size in each stratum is weighted by its population distribution. Therefore, variability of sample sizes in the subgroups will be reduced to zero (Shrout & Napier, 2010).

Rotated Questionnaire Designs

Complex surveys may cover multiple content domains or constructs and, therefore, include many items, tasks, and survey questions. To reduce the assessment load for participants, some of these surveys divide the item pool into blocks or clusters of items. Ultimately, each participant receives only a subset of what comprises the total assessment pool (Rutkowski et al.,

2010). Although such rotated questionnaire designs minimize assessment time, they challenge the estimation of scale scores, particularly concerning the accuracy and comparability of the results at the participant level. Some complex surveys in education use the plausible-values technique to ensure that accurate population estimates of students' proficiency can be generated from the data of rotated questionnaire designs (Laukaityte & Wiberg, 2017). This approach estimates a proficiency distribution via multiple imputation and randomly draws likely proficiency scores, plausible values, from it (von Davier et al., 2009). These plausible values then are used as representations of participants' proficiency.

As in multiply imputed data sets, analysis of complex survey data with plausible values requires conducting the data analysis for each set of plausible values. The resultant model parameters of interest then are pooled via Rubin's (1987) combination rules. The incorrect use of plausible values, for instance, using only one plausible value or an average of all plausible values before the data analysis, underestimates the uncertainty of proficiency estimates and within-school variance (Laukaityte & Wiberg, 2017; von Davier et al., 2009), and overestimates the relationships to other variables (Mislevy et al., 1992).

Two-Stage IPD Meta-Analysis of Complex Sampling Surveys

Description of the Approach

To synthesize IPD from complex sampling surveys, we propose a two-stage IPD meta-analytic approach that addresses the complexities of the primary survey data and the secondary meta-analytic data. As noted earlier, two-stage IPD meta-analysis has several advantages over the one-stage approach for the analysis of complex survey data. In one-stage IPD meta-analysis, data from all studies are analyzed simultaneously, taking into account the clustering of participants within studies (Burke et al., 2017; Debray et al., 2015). However, if raw participant

data are already clustered, multilevel models with hierarchical (e.g., participant data nested in schools and studies) or cross-classified (e.g., participant data nested in schools and studies, and in outcome variables) structures must be specified to derive effect sizes of interest and their heterogeneity. Estimating such models is (still) computationally demanding and often not feasible with large data sets (Cheung & Jak, 2016; Declercq et al., 2020). In addition, the one-stage approach requires harmonized metrics for measures across studies to pool the IPD within a single model. The implementation of harmonization procedures depends on the availability and quality of the measures applied, and, as a result, the one-step approach may not be feasible in many situations (e.g., when different sets of items were administered across studies to create a measurement model). In contrast, the two-stage approach is simpler because it requires only a commensurate metric for the effect sizes (Brunner et al., 2022). Yet, measurement heterogeneity can still be investigated in the two-stage approach through moderator analyses (e.g., via mixed-effects meta-regression models) in stage 2. Finally, complex survey data from two or more primary studies may be based on different complex survey designs (e.g., different sampling procedures, stages, clusters, and weights). These differences challenge the meaningful combination of IPD in the one-stage approach and may require a differential treatment of the primary study data. A one-stage IPD meta-analysis would not handle the different sample designs (e.g., different types of weights or sampling stages) across all studies. A two-stage IPD meta-analysis can address this issue as follows: During the first stage, the cluster sampling, stratification, and sampling weights can be incorporated directly while analyzing the IPD separately and generating the effect sizes of interest and their sampling variances. These effect size and variance estimates are then meta-analyzed during the second stage. In the context of big data meta-analysis, this two-stage, parameter-based approach is referred to as the

Split/Analyze/Meta-Analyze (SAM) approach (Cheung & Jak, 2016) and can also be considered a form of integrative data analysis (Wilcox & Wang, 2021). The approach enables researchers to account for the features of complex survey data and derive model- and design-based effect sizes and variance estimates (Cooper & Patall, 2009; Eisenhauer, 2021; Tierney et al., 2015).

Moreover, researchers may use the type of design as a moderator to test whether the design has any impact on the effect sizes. In the following section, we present the analytic options within the two stages of an IPD meta-analysis of complex survey data.

Stage 1: Model- and Design-Based Generation of Effect Sizes and Sampling (Co-)Variances

In Stage 1, raw participant data from each study are analyzed separately, yet based on the same analytic model to ensure comparability of the resultant effect sizes. Selection of the analytic model depends on the research questions and the type of data of interest. Nevertheless, each study's complex sampling design can be incorporated directly into data analysis under a design- or model-based approach. The *design-based approach* corrects for the complex sampling design by re-estimating sampling variances and standard errors in models without multiple analytic levels. Taylor series linearization (Lumley, 2004), replication methods (Rust, 2013), normalized weights (Cavin & Ohls, 1990), test statistics adjustments (Thomas & Heck, 2001), and effect size corrections (Hedges, 2007) are some strategies that can be used to account for the dependencies of the data using a design-based strategy. The *model-based approach* partitions the variances in the variables of interest into their components at multiple analytic levels. Multilevel modeling procedures—such as multilevel regression, multilevel latent profile analysis, or multilevel structural equation modeling—estimate the effects between and within clusters simultaneously (see Hox et al., 2017). Typically, the sampling (co-)variances are extracted from

the resultant, asymptotic sampling covariance matrix (e.g., Cheung & Jak, 2016; Kwan & Chan, 2011).

Unlike the first stage of the two-stage IPD meta-analysis without complex survey data, the first stage of the two-stage IPD meta-analysis with complex survey data requires an explicit adjustment or modeling of the effect size and variance estimates incorporating the design features of the complex surveys. Most SEM packages can handle missing, categorical, and non-normal data appropriately at this stage. After fitting the appropriate models, effect sizes and their sampling variance-covariance matrices can be automatically derived via the SEM packages (Cheung, 2018). Regardless of the approach used, Stage 1 results in K model- and design-based effect sizes ($\theta_k, k = 1, \dots, K$), and their sampling variances (v_k) or respective covariances. These sampling variances and covariances are treated as known in the second stage analysis.

Stage 2: Meta-Analytic Synthesis of Effect Sizes

In Stage 2, meta-analytic techniques come into play to estimate pooled effect sizes, indices of heterogeneity, and moderator effects. Given that complex survey data often include multiple groups of participants, such as countries, regions, assessment cycles, or outcome measures, stage 1 may elicit effect size multiplicity. For instance, if researchers wish to synthesize gender differences in mathematics achievement for students in primary and secondary schools, they may draw from the data of multiple complex surveys in education, such as PISA and TIMSS. Each of these surveys includes multiple countries (e.g., 65 participating countries and economies are part of PISA 2012), grade levels (e.g., TIMSS grades 4 and 8), and cycles (e.g., seven PISA cycles between 2000 and 2018 assessing mathematics achievement) and thus provide multiple effect sizes per individual participant data set. Ignoring this effect size

multiplicity and the possible statistical dependencies among effect sizes in the meta-analytic models can provide misleading results (e.g., López-López et al., 2018; Scammacca et al., 2014).

The structure of dependent effect sizes can be classified broadly into *correlated* and *hierarchical* structures (Pustejovsky & Tipton, 2021). In correlated structures, sampling errors are correlated because multiple effect sizes are calculated using the same participants and samples (Cheung, 2019). For example, complex surveys in education, such as PISA, gather information on educational achievement in multiple domains (e.g., mathematics, science, and reading) among the same students. Effect sizes representing gender differences in these multiple domains within the same samples can be viewed as correlated. Hierarchical structures typically result from data in which effect sizes from multiple, independent samples or groups are nested within primary studies. Random effects are conditionally dependent on such structures because effect sizes within a cluster are likely to be more similar to each other than effect sizes across clusters. For example, multiple labs may have conducted an intervention with multiple, independent samples of participants to study the replication of effects (Kvarven et al., 2020). This scenario describes a hierarchical data structure (i.e., independent samples nested in labs) and allows meta-analysts to quantify heterogeneity within and between labs.

More complex statistical dependencies may emerge when combining effect sizes from complex surveys. For instance, a meta-analyst may synthesize effect sizes from multiple, independent participant samples on multiple outcome measures. The meta-analytic data structure in this example follows both a correlated *and* hierarchical structure. Another meta-analyst may include effect sizes from samples in multiple countries within a complex survey (e.g., 65 countries in PISA 2012) and draw from several survey cycles (e.g., PISA 2003, 2012, and 2022). In this scenario, the meta-analytic data may indicate time and country dependencies, and could

be represented by a cross-classified structure with effect sizes nested in countries and survey cycles (Fernández-Castilla et al., 2019). Notably, the complexity of the complex survey designs can impact both the primary and meta-analytic data structures. Simultaneously, these two structures may differ, as they represent different analytic levels. For instance, while the primary PISA data in our last example followed a nested structure, with participants nested in schools and countries, the meta-analytic data do not incorporate participant and school levels, but do incorporate levels of effect sizes, survey cycles, and countries. Therefore, it is critical to distinguish between primary and meta-analytic data in the two-stage approach (Scammacca et al., 2014).

To summarize, effect size multiplicity in meta-analytic data sets from complex surveys can be due to the inclusion of multiple surveys, multiple survey cycles, multiple participant populations, or multiple outcomes or dependent effect sizes. Typical situations with meta-analytic data from complex surveys may include, but are not limited to (e.g., Scherer et al., 2021; Brunner et al., 2022): (a) Effect sizes from multiple surveys (e.g., TIMSS 2015 and PISA 2015); (b) Effect sizes from a single survey and multiple cycles (e.g., TIMSS 2011, 2015, and 2019); (c) Effect sizes from multiple surveys and multiple cycles (e.g., PISA 2012, PISA 2015, TIMSS 2011, TIMSS 2015); (d) Effect sizes from multiple dependent outcomes and the same samples (e.g., gender differences in reading, mathematics, and science in PISA 2018). To identify the appropriate meta-analytic data structure and meta-analytic model, meta-analysts should review the hierarchical and/or correlational nature of these multiplicities. Oftentimes, the data structure involves more than one source of multiplicity and requires meta-analytic working models beyond the standard random-effects model.

Several meta-analytic working models can handle effect size multiplicity (Cheung, 2019; López-López et al., 2018; Pustejovsky & Tipton, 2021). The selection of a meta-analytic model involves three key decisions: First, choosing an assumption for the within-study correlation between effect size estimates. Second, identifying a structure for the random effects. Third, determining whether to include any additional analytic levels (Pustejovsky & Tipton, 2021). Understanding the data structure and data-generating processes is necessary for selecting an appropriate model. In the following section, we provide an overview of the meta-analytic working models that synthesize effect sizes from complex survey data during stage 2.

Multivariate meta-analytic models. In the presence of within-study correlated effects, researchers can address these dependencies via multivariate meta-analysis (Cheung, 2013; Wei & Higgins, 2013). Multivariate meta-analysis incorporates a sampling covariance matrix $\mathbf{V}_k$ for each primary study k that is assumed to be known and that carries information about the extent to which any two effect sizes are correlated. A multivariate random-effects model decomposes the vector of observed effect sizes $\boldsymbol{\beta}_k$ into the vector of the average population effects μ , sampling errors $\mathbf{r}_k$, and random effects $\mathbf{u}_k$ ($k = 1, \dots, K$):

$$\boldsymbol{\beta}_k = \mu + \mathbf{u}_k + \mathbf{r}_k$$

$$\mathbf{r}_k \sim MVN(\mathbf{0}, \mathbf{V}_k) \text{ and } \mathbf{u}_k \sim MVN(\mathbf{0}, \mathbf{T}^2)$$

with $\mathbf{T}^2$ representing the population heterogeneity covariance matrix that has to be estimated, and $\mathbf{V}_k$ representing the known sampling covariance matrix (Mavridis & Salanti, 2013). Notably, the matrix $\mathbf{T}^2$ can have different structures (e.g., unstructured, diagonal, compound symmetric, zero), which reflect on the researchers' assumptions about the correlated effects (Cheung, 2013). As raw data are available in an IPD meta-analysis, the sampling covariance matrix can be estimated during Stage 1.

The following example describes a typical scenario in which multivariate meta-analysis could be employed to handle correlated effects in the context of complex surveys: Suppose researchers are interested in synthesizing gender differences in students' mathematics, science, and reading achievement. Utilizing PISA 2018 data from multiple participating countries or economies, they can generate respective effect sizes for each of the three domains and estimate sampling variances and covariances from the IPD. Subsequent multivariate meta-analysis pools the effect sizes for multiple outcomes from the same sample and quantify between-country heterogeneity by taking into account the correlations among the multiple effect sizes.

Multilevel meta-analytic models. Multilevel meta-analysis can handle nested effect sizes with both hierarchical and non-hierarchical structures. For each study, it is assumed that there is a single true effect size of interest, and each study provides a single estimate of that effect size derived from one sample of participants. Multilevel meta-analysis extends the common random-effects model by adding analytic levels with hierarchical or non-hierarchical structures (Van den Noortgate et al., 2015).

Three-level random-effects models. The sampling variance for each effect size β_{jk} in primary study k is modelled at Level 1, within-study heterogeneity (i.e., variation between samples $j = 1, \dots, J$ within study k) is modelled at Level 2, and between-study heterogeneity is modelled at Level 3:

$$\text{Level 1 (sampling variance):} \quad \beta_{jk} = \theta_{jk} + r_{jk}$$

$$\text{Level 2 (within studies):} \quad \theta_{jk} = \lambda_k + q_{jk}$$

$$\text{Level 3 (between studies):} \quad \lambda_k = \mu + u_k$$

In this model specification, θ_{jk} is the true effect size of sample j in study k , r_{jk} follows a normal distribution with known sampling variance $r_{jk} \sim N(0, \sigma_r^2)$, λ_k is the average effect in the k th study

with residuals $q_{jk} \sim N(0, \sigma_q^2)$, and μ is the average population effect size with residuals $u_k \sim N(0, \sigma_u^2)$. The random effects are assumed to be mutually independent, and the structure is hierarchical.

In the context of complex surveys, researchers might want to synthesize multiple, sample-specific effect sizes across surveys or survey cycles. For example, researchers seeking to synthesize the relation between students' socioeconomic status and mathematics proficiency can utilize the data from multiple international large-scale assessments in education (e.g., PISA, TIMSS). In this scenario, each sample provides an effect size, yet each survey includes multiple samples (e.g., samples from multiple participating countries). Assuming that these samples are conditionally independent, the meta-analytic data structure is represented by models accounting for hierarchical effects, such as multilevel random-effects models (Fernández-Castilla et al., 2020). However, if the number of clusters (e.g., surveys or survey cycles) is small, then researchers may consider subgroup analyses rather than a multilevel meta-analytic model (e.g., Harrer et al., 2021).

The mathematical formulations of multivariate and multilevel meta-analytic models are closely related (Cheung, 2015; Section 6.4). A hierarchical structure can be reorganized as a multivariate structure. Furthermore, a multivariate structure can be approximated by a hierarchical structure when estimates of sampling covariances are unavailable. Simulation studies (López-López et al., 2018; Van den Noortgate et al., 2013) show that this approximation works reasonably well in many settings.

Cross-classified random-effects models. Cross-classified random-effects models deal with situations in which the meta-analytic data structure is not purely hierarchical (Fernández-Castilla et al., 2019). These meta-analytic models can be specified as multilevel meta-analytic

models, but with crossed, rather than hierarchical random effects. Cross-classified random effects can be found when synthesizing IPD from multiple complex surveys (e.g., multiple cycles of the same survey or multiple different surveys). For example, meta-analysts who wish to synthesize gender differences in reading achievement for students in primary and secondary schools can include several cycles and surveys of the educational large-scale assessments, such as PIRLS and PISA. In this scenario, each survey includes multiple cycles (e.g., five PIRLS cycles between 2001 and 2021 and seven PISA cycles between 2000 and 2018), and countries (e.g., 70 countries in PIRLS 2021 and 79 countries in PISA 2018) and thus provide multiple effect sizes per individual participant data set. Given that countries participate in multiple cycles and surveys, samples are not only nested in surveys but also in countries, and countries may contribute effect sizes for multiple studies. Thus, the study and country levels may co-exist independently. Cross-classified random-effects model represent this meta-analytic data structure and quantify variations between samples within studies, between samples within countries, between studies, and between countries. For samples j , studies k , and countries l , a cross-classified random-effects model can be specified with $r_{j(kl)} \sim N(0, \sigma_r^2)$, $q_{j(kl)} \sim N(0, \sigma_q^2)$, $u_k \sim N(0, \sigma_u^2)$, $p_l \sim N(0, \sigma_p^2)$, and mutually independent random effects as:

$$\text{Level 1 (sampling variance):} \quad \beta_{j(kl)} = \theta_{j(kl)} + r_{j(kl)}$$

$$\text{Level 2 (within studies):} \quad \theta_{j(kl)} = \lambda_{(kl)} + q_{j(kl)}$$

$$\text{Levels 3 and 4 (between studies or countries):} \quad \lambda_{(kl)} = \mu + u_k + p_l$$

This decomposition of the variances sheds light on the levels at which heterogeneity might be located. Heterogeneity can be completely at random, localized at multiple analytic levels (e.g., within or across studies), or associated with study, sample, or measurement characteristics

(Viechtbauer, 2010). Hence, meta-analysts can extend the multilevel working models to mixed-effects meta-regression models and test for possible moderator effects.

Robust Variance Estimation (RVE). RVE provides valid standard errors in point estimates, interval estimates, and significance tests in meta-analytic models without requiring knowledge of dependent estimates' correlation structures (Hedges et al., 2010; Tipton, 2013, 2015). In this approach, a working model is selected to model the dependence structure.

Correlated effects models incorporate a within-study correlation ρ of the effect sizes as

$Cov(r_{jk}, r_{hk}) = \rho s_k^2$, with s_k^2 representing average sampling variance in study k —a variance that

is part of the meta-analytic weights. *Hierarchical effects models* incorporate estimates of the within- and between-study variances and corresponding weights. It is assumed further that,

conditional on being in the same study, the effect size estimates within studies are independent,

$Cov(r_{jk}, r_{hk}) = 0$. Meta-analytic data sets may also include both correlated *and* hierarchical

effects. In this situation, researchers can extend hierarchical effects models through, for instance,

a constant sampling correlation ρ between pairs of effect sizes, assuming that this correlation is

the same across all studies. Robust variance estimation procedures is particularly useful in

situations in which information about the sampling covariance matrix in each study is not

available, the assumptions on the normality of residuals are not met (Hedges et al., 2010), only

few studies are included in the meta-analysis, or the primary research interest does not lie in the

study- and case-level variance estimates (Moeyaert et al., 2017).

Step-by-Step Tutorial

To illustrate the application of a two-stage IPD meta-analysis of complex survey data, we provide two examples, following a stepwise procedure that implements the two analytic stages (see Table 1). These examples showcase the utility of the two-stage approach to (a) handle

complex survey sampling designs in stage 1; (b) allow for a model-based generation of effect sizes; (c) generate complex types of effect sizes (e.g., contextual effects); (d) account for the complex data structure during the meta-analysis in stage 2; and (e) combine AD with IPD from complex sampling surveys. Each of these examples is accompanied by online material, which can be accessed via the Open Science Framework at <https://osf.io/58eca/>. This material contains the analytic codes and outputs of the stage-1 and stage-2 analyses.

Illustrative Example 1: Synthesizing IPD from Multiple Complex Surveys

Purpose of the Example

Our first illustrative example focuses on the Big-Fish-Little-Pond Effect (BFLPE) in mathematics—that is, the negative contextual effect of classroom mathematics achievement on students’ mathematics self-concept (Marsh et al., 2008)—and examines its heterogeneity across countries and over time. The example synthesizes data from multiple complex sampling surveys, that is, multiple cycles of Trends in International Mathematics and Science Study (TIMSS). We show how model-based effect sizes of the BFLPE can be generated in stage 1 by multilevel structural equation modeling and incorporating the multi-stage sampling design elements of the primary data (i.e., sampling weights, plausible values representing student achievement, clustering of student data in classrooms, grouping by countries, stratification). Illustrating stage 2, we submitted the model-based effect sizes and their sampling variances to random-effects meta-analysis and mixed-effects meta-regression. This stage resulted in evidence of the heterogeneity of the BFLPE and possible explanatory variables thereof. We show how to implement the two stages in the software *Mplus* (Muthén & Muthén, 1998-2017), the R package *MplusAutomation* (Hallquist & Wiley, 2018), and the R package *metafor* (Viechtbauer, 2010).

Step 1: Problem Formulation and Framing of the Meta-Analysis

As any other meta-analysis, an IPD meta-analysis of complex survey data begins with defining the research questions, framing the meta-analysis, and delineating the sources and procedures needed to find relevant evidence. To support the formulation of research questions and delineate the review's scope, meta-analysts can access several frameworks that define the core elements they need to consider (e.g., PICO/PECO framework; see Thomas et al., 2019). Ultimately, these specifications define inclusion and exclusion criteria, as well as development of a search strategy. Inclusion and exclusion criteria may be set based on study design and sampling design features, such as the primary cluster unit (e.g., geographical location, school, or classroom), inference type (e.g., population- vs. sampling-based), study design (e.g., cross-sectional or longitudinal design), or specific features of the complex data structure (i.e., multistage sampling, cluster sampling, or stratification). For a more detailed description of these elements, we kindly refer readers to standard literature on systematic reviews and meta-analyses (e.g., Card, 2015; Higgins et al., 2019). Meta-analysts may consider pre-registering their IPD meta-analyses during this step (Moreau & Gamble, 2022).

As noted earlier, our illustrative example focuses on the negative contextual effect of classroom mathematics achievement on students' mathematics self-concept, BFLPE, in elementary school students. Although the existing body of evidence broadly supports the existence of the BFLPE (Marsh et al., 2014, 2015), there are exceptions (Sung et al., 2014). Thus, the goals of this IPD meta-analysis were to synthesize evidence on BFLPE from complex survey data into a pooled effect size, quantify its heterogeneity across countries and over time, and explore possible moderator effects from cultural dimensions and economic development, guided by these research questions (RQs):

- RQ1. To what extent is class-average student achievement in mathematics related to individual students' mathematics self-concept after controlling for students' individual mathematics performance in primary school (BFLPE)?*
- RQ2. To what extent does BFLPE vary across countries and over time?*
- RQ3. To what extent can Hofstede's country indicators of cultural dimensions and countries' economic development explain this variation?*

We set the following inclusion criteria: IPD must (a) be based on student populations in primary school; (b) contain a scale measuring mathematics achievement; (c) contain a scale measuring mathematics self-concept; (d) contain information about the clustering of students in classrooms (i.e., identifiers of the classroom and on the student level); and (e) be based on international surveys. Given these specifications, our search strategy included institutional and international data repositories (ILSA-Gateway, OECD, and IEA) and a computerized database search in the electronic database ERIC using the search terms “International large-scale assessment” AND “Mathematics achievement” AND “Self-concept.” An illustrative preregistration defining the variables of interest, search strategy, and analysis was stored in the OSF (<https://osf.io/yt7q3/>).

Step 2: Data Search and Selection

In the next step, researchers identify, screen, and select IPD from complex surveys. Searches can be conducted as targeted searches in institutional and governmental databases to identify IPD directly and computerized database searches to identify publications presenting possible secondary analyses of IPD. Having screened the resultant data against the inclusion and exclusion criteria, researchers then may extract data and any supplementary information (e.g., codebooks, original questionnaires). As in any meta-analysis, this step requires thorough

documentation to achieve maximal replicability, for instance, guided by PRISMA statement and flowchart for IPD meta-analyses (Stewart et al., 2015).

In our illustrative example, we conducted searches in major IPD databases of international large-scale assessments in education, including the OECD's PISA database (<https://www.oecd.org/pisa/data/>) and the International Association for the Evaluation of Educational Achievement website (<https://timssandpirls.bc.edu/timss-landing.html>). The additional database search for publications that may point to further IPD from complex surveys yielded 56 publications. Figure 1 provides an overview of the search and selection process, along with the number of publications and unique international large-scale assessments identified during each stage. Only the Trends in International Mathematics and Science Study (TIMSS) data since 2003 met all inclusion criteria, and we included student data from five TIMSS cycles: 2003, 2007, 2011, 2015, and 2019.

Step 3: Data Preparation

During this step, IPD are prepared for analysis and synthesis. Meta-analysts should pay particular attention to the appropriate selection and coding of variables that represent the constructs of interest and variables that represent the complex data structure (e.g., clustering identifiers, sampling weights, jackknife weights, plausible values), and refer to the complex survey documentation to ensure that the features of the study are correctly coded. For our illustration, we used the R packages EdSurvey (Bailey et al., 2021) and tidyverse (Wickham et al., 2019) to extract, clean, and recode IPD from each TIMSS cycle. We identified and extracted indicators of mathematics achievement (i.e., five plausible values) and self-concept (i.e., responses to four Likert-scale items, two of which were recoded due to their negative wording), along with student, classroom, and country identifiers, and sampling weights for students and

classrooms from the TIMSS data sets. We rescaled student and classroom weights following Wang's (2020) recommendation. Table 2 illustrates the structure of the resultant data.

Finally, we extracted and coded country-level variables in a separate data set. Specifically, we obtained the countries' Human Development Index (HDI) scores from the United Nations database (<http://hdr.undp.org/en/data>) and their scores on the six cultural dimensions (i.e., individualism-collectivism, power distance, uncertainty avoidance, masculinity-femininity, long-term vs. short-term orientation, and indulgence-restraint; <https://www.hofstede-insights.com/product/compare-countries/>), as developed by Hofstede et al. (2010).

Step 4: Analysis of IPD and Estimation of Effect Sizes

During this step, meta-analysts generate the effect sizes of interest while accounting for the complex nature of the IPD—this corresponds to Stage 1 of the two-stage IPD meta-analysis. Typically, this step involves choosing an analytic model to estimate effect sizes of interest from IPD. Instead of extracting effect sizes directly from IPD reports that may rely on different analytic models, one unifying model is applied to each IPD set to ensure that effect size has the same meaning across data sets (Cheung & Jak, 2016; Stapleton et al., 2016).

Considering that IPD may have missing data, meta-analysts must make decisions on how to handle this. Missingness can have multiple causes in complex surveys, such as response fatigue, random skipping of questions, or design features (Buuren, 2018). For instance, in the PISA 2012 survey, the three versions of the student background questionnaire followed a rotated design such that every student received two-thirds of the questions with some anchoring items (OECD, 2014). If meta-analysts want to analyze such questionnaire data, they may draw from modern techniques to handle missing data, such as multiple imputation or the model-based full-information-maximum-likelihood (FIML) procedure (Brunner et al., 2022). These techniques can

accommodate the complexities of complex surveys, such as their multilevel data structures (Enders et al., 2016).

With most complex surveys including multiple countries or populations, the availability of IPD with the same measures across data sets further allows meta-analysts to examine and establish the comparability of the measures across these groups, for instance via measurement invariance testing (Curran & Hussong, 2009). In this way, possible heterogeneity that might be due to differences in measurement models can be reduced. In the context of complex sampling surveys, testing for different levels of measurement invariance requires taking into consideration the complexities of the data, not only when deciding on an invariance model based on changes in fit indices (Rutkowski & Svetina, 2014), but also when specifying measurement models. For instance, meta-analysts can take a model-based approach to represent the hierarchical structure of complex survey data (Snijders & Bosker, 2012). Thus, measurement models may be specified at multiple analytic levels (e.g., representing the self-concept construct at the student and classroom levels), thereby extending the possibilities of non-invariance. With multiple groups and levels, testing for invariance involves both cross-group *and* cross-level invariance (Jak, 2019; Ryu, 2014). Having established that the measures have the same meaning across groups or studies, meta-analysts can estimate effect sizes from their analytic models and extract respective sampling variances.

In our illustrative example, we took a model-based approach to account for the complex sampling features of the data and estimate the BFLPE. Considering that we relied on students' responses to the self-concept questions, we first developed a measurement model for mathematics self-concept and tested it for its cross-level and cross-country invariance within each TIMSS cycle via multi-group, multilevel confirmatory factor analysis (MG-MCFA; see

Ryu, 2014). Second, we estimated a multi-group, two-level, latent covariate model to generate standardized BFLPE sizes for each country within each TIMSS cycle (see Marsh et al., 2009).

Missing data were handled via the FIML procedure in *Mplus*.

Establishing a measurement model. First, we estimated a configural invariance model with one factor for mathematics self-concept at the student and classroom levels, a residual covariance between negatively worded items (*asbm03b* with *asbm03c*), and factor loadings that could vary across levels and countries. Second, we constrained the factor loadings to be invariant across countries at the student level. Third, we added the constraint of equal factor loadings across countries at the classroom level, but allowed factor loadings to vary across levels. Finally, we estimated a model with equal factor loadings across countries and levels. This MG-MCFA model resulted in good overall fit for each TIMSS cycle, which differed to an acceptable extent from previous models' fit (Kim et al., 2012; see Table 3).

The estimation of the measurement invariance models incorporated the data sets' complex sampling features. We used the `mplusObject` function to set up the analytic *Mplus* code with sampling weights, clustering, and grouping by country:

```
bflpe_timss2003 <- mplusObject (
  TITLE = "Model estimating the BFLPE for TIMSS 2003",
  VARIABLE =
    "USEVARIABLES ARE asbm03a asbm03b asbm03c asbm03d;
  MISSING ARE ALL (-999);
  WEIGHT = studentweight;
  WTSCALE = cluster;
  BWEIGHT = classroomweight;
  BWTSCALE = sample;
```

```

CLUSTER = schoolid idclass;

GROUPING IS idcntry 51=ARM 36=AUS 956=BFL 9132=COT 9133=CQU
196=CYP 926=ENG 344=HKG 348=HUN 364=IRN 380=ITA 392=JPN
440=LTU 428=LVA 504=MAR 498=MDA 528=NLD 578=NOR 554=NZL
608=PHL 643=RUS 927=SCO 702=SGP 705=SVN 788=TUN 158=TWN
11800=UIN 840=USA 887=YEM) ; ",

ANALYSIS =

"type = TWOLEVEL;

ESTIMATOR = MLR"; [...]
```

The **WEIGHT** command specifies the student-level weights with cluster scaling (**WTSCALE=cluster**), and the **BWEIGHT** command specifies classroom weights with sample scaling (**BWTSCALE=sample**; Asparouhov, 2005). The **CLUSTER** and **GROUPING** commands define the additional analytic levels (i.e., classroom level) and the multi-group structure by country. The command lines **TYPE=TWOLEVEL** and **ESTIMATOR=MLR** set the analyses to multilevel analyses with robust maximum-likelihood estimation.

Model-based generation of effect sizes. We fitted a two-level latent covariate model to estimate the BFLPE (Lüdtke et al., 2008). This model extended the MG-MCFA with cross-level and cross-country measurement invariance for each TIMSS cycle by adding mathematics achievement as the outcome variable at the student and classroom levels (see Figure 2). While the measurement model of mathematics self-concept was constrained to metric cross-level and cross-country invariance, the structural coefficients were uniquely for each participating country within a TIMSS cycle:

```

MODEL = "

%WITHIN%
```

```

! Measurement model

ASCS_W BY asbm03a-asbm03d (ASCM1-ASCM4);

asbm03b with asbm03c;

! Structural model

ASCS_W ON asmmat;

! Variances

ASCS_W; asmmat;

%BETWEEN%

! Measurement model

ASCS_B BY asbm03a-asbm03d (ASCM1-ASCM4);

asbm03b with asbm03c;

! Structural model

ASCS_B ON asmmat;

! Variances

asmmat; ASCS_B;

MODEL ARM:

! Model for ARM Armenia

%WITHIN%

ASCS_W ON asmmat (ARM_b1);

asmmat (ARM_wvar1); ASCS_W (ARM_wvar2);

%BETWEEN%

ASCS_B ON asmmat (ARM_b2);

asmmat (ARM_bvar1); ASCS_B (ARM_bvar2);

! Freely estimate the item intercepts

[asbm03a-asbm03d*];

! Constrain the factor means to identify the mean structure

```

[ASCS_B@0]; [...]

The standardized effect size of the BFLPE can be calculated as (Marsh et al., 2009):

$$BFLPE = 2 \times (\beta_{between} - \beta_{within}) \times \sqrt{Var(math_{bj})} / \sqrt{Var(math_{bj}) + Var(scw_{ij}) + Var(math_{ij}) + Var(sc_{bj})}$$

Where $\beta_{between}$ is the unstandardized regression coefficient of school average mathematics achievement on school average mathematics self-concept, β_{within} is the unstandardized regression coefficient of student mathematics achievement on student mathematics self-concept, $Var(math_{bj})$, $Var(math_{ij})$, $Var(sc_{bj})$, and $Var(scw_{ij})$ are the variances of the between-level mathematics achievement, within-level mathematics achievement, the between-level self-concept, and the within-level self-concept, respectively. Using the MODELCONSTRAINT command, we computed the country-specific BFLPE sizes from the respective structural parameters and variance components in the model. This effect size describes the difference in the dependent variable between two groups that differ by predictor variables by two standard deviations (Marsh et al., 2009):

```
MODELCONSTRAINT = "
! Model for Armenia (ARM)
new(st_bflpe);
st_bflpe = 2*(ARM_b2-
ARM_b1)*(sqrt(ARM_bvar1))/(sqrt(ARM_bvar1*ARM_b2**2+
ARM_bvar2+ARM_wvar1*ARM_b1**2+ARM_wvar2));", [...]
```

Finally, the TECH3 output contained the asymptotic covariance matrix and provided country-specific estimates of the sampling variances for each effect size (e.g., Cheung, 2009).

Given that each TIMSS data set contained multiple plausible values, we estimated the model for each of the plausible-value data sets and combined the resultant model parameters via Rubin's combination rules (Laukaityte & Wiberg, 2017). The `IMPUTED=TRUE` command ensures that the model is estimated separately for each of the five plausible-value data sets. A text file (`timss_2003_dat`) with the names of the data sets containing the plausible values needs to be submitted to the `RDATA` command:

```
OUTPUT = "STDYX; ! Fully standardized solution
TECH3; ! Extract the asymptotic covariance matrix",
rdata = timss_2003_dat,
imputed = TRUE)
```

Step 5: Meta-Analysis of the Effect Sizes

Having extracted effect sizes and respective sampling variances from IPD, the next step implements Stage 2 of the two-stage IPD meta-analysis with complex survey data—synthesizing effect sizes, quantifying their heterogeneity, and examining possible moderator effects with meta-analytic techniques. To accomplish these tasks, it is necessary to create a meta-analytic data set with the estimated effect sizes and sampling variances, potential moderators, and identifiers indicating the data structure. Ultimately, researchers can estimate a weighted average effect size and its heterogeneity based on an appropriate meta-analytic baseline model. The selection of this model should be guided by the nature of the data structure and the types of effect size multiplicity (see López-López et al., 2018). Although IPD complexities were mainly accounted for in the primary data analysis, they also impact the stage-2 analysis of the meta-analytic data.

Analyzing selection (publication) bias and file-drawer issues is key to understanding possible threats concerning IPD meta-analysis validity (e.g., Borenstein et al., 2021; Simonsohn

et al., 2014). Finally, sensitivity analyses and robustness checks are tools that further strengthen the validity argument underlying the meta-analytic findings (Deeks et al., 2019). In the following section, we illustrate these elements for the BFLPE example.

Creating a meta-analytic data set. To build a meta-analytic BFLPE data set, we first extracted each study's BFLPE sizes and sampling variance estimates. To establish the context of these estimates, we added further identifiers of effect sizes, TIMSS cycles, and countries. Second, we merged this data set with the coded country-level variables (see Step 3). Table 4 provides an overview of the final, meta-analytic data structure.

Description of primary IPD. The meta-analytic sample contained 85 independent samples from five studies (TIMSS cycles), yielding 248 effect sizes from a total sample of 1,237,286 students. About 48% of the samples originated from Europe, followed by 30% from Asia, 15% from the Americas, 5% from Africa, and 2% from Australia. The sample sizes within countries ranged between 1,731 and 25,173, with an average of $M = 4,974.3$ ($SD = 2,434.6$, $Mdn = 4,337$).

Meta-analytic baseline model. To synthesize BFLPE, we established a baseline model that represented the structure of the meta-analytic data set and accounted for effect size multiplicity. Considering that each country sample provided one effect size per TIMSS cycle, and that some countries participated in multiple TIMSS cycles, the nature of the effects is both hierarchical and correlational. To examine the extent to which heterogeneity exists across countries and TIMSS cycles, we tested five baseline models (see Table 6). Model 1 represents a standard random-effects model that ignored the issue of effect size multiplicity and assumed that effect sizes are independent. Models 2 and 3 represent three-level random-effects models with sampling variation at Level 1; variations between effect sizes, but within countries (cycles) at

Level 2; and variation between countries (cycles) at Level 3 (see Figure 3). These two models assumed the hierarchical nesting of effects in countries (cycles). Addressing possible correlational effects over time (i.e., due to some countries participating in multiples survey cycles), we extended Model 2 by incorporating a constant sampling correlation (ρ); the resultant Model 4 represents a CHE working model (Pustejovsky et al., 2021). We assumed ρ to be 0.5; however, meta-analysts may choose this coefficient differently depending on the information they have available about the dependencies of effects over time. Finally, we specified a four-level random-effects model with a cross-classified structure that accounted for the nesting of effect sizes in countries and TIMSS cycles (Model 5).

We implemented these models using the `rma.mv` function in the R package `metafor` (Viechtbauer, 2010). Table 5 shows the respective model specification codes. In all models, we first specified the vector of observed effect sizes (`effect_size`) and the corresponding sampling variances (`var`) via the `yi` and `V` arguments. Second, we specified the random effects in the model, addressing the hierarchical data structure. For instance, in Model 2, the random effects were based on a hierarchical structure with effect sizes nested in countries. This structure can be specified via `random=list(~1|country/ESID)`. In the cross-classified Model 5, two independent nesting levels existed, and the respective random effects were represented by `random=list(~1|country/ESID, ~1|year)`. Notice that specification of random effects is the same in Models 2 and 4; these models both represent three-level random-effects models accounting for hierarchical effects. However, instead of the vector of sampling variances (`var`), Model 4 used a sampling covariance matrix (`V_mat`) as the input for the `V` argument. We generated this covariance matrix in the R package `clubSandwich` (Pustejovsky, 2021) via the `impute_covariance_matrix` function to which sampling variances (`var`), constant

sampling correlation (`rho`), and the clustering variable identifier (`country`) are submitted. Furthermore, we obtained cluster-robust standard errors and confidence intervals using the `conf_int` function.

Table 6 displays average effect sizes, variance components, and heterogeneity indices. Across the models, weighted average effect sizes for BFLPE ranged between $\hat{\mu} = -0.458$ (Models 1 and 3) and $\hat{\mu} = -0.451$ (Model 2), indicating a significant and negative BFLPE. All models exhibited heterogeneity in effect sizes, but to different degrees. For instance, while Model 2 revealed that most of the heterogeneity lies between, rather than within countries ($I_{ES}^2 = 12.1\%$, $I_C^2 = 70.0\%$), Models 3 and 5 revealed that hardly any variation across the TIMSS cycles existed ($I_Y^2 = 0.0\text{--}0.2\%$). Further model comparisons demonstrated that Model 2 had a better fit than Model 1, $\chi^2(1) = 116.2$, $p < .001$. However, Model 3 did not outperform Model 1, $\chi^2(1) = 0.0$, $p = 1.00$. Thus, while there was evidence of between-country variation, there was no evidence of between-cycle variation independent of the countries. Model 5 incorporated both country and cycle structures and exhibited better fit than Model 1 ($\chi^2[1] = 117.8$, $p < .001$), yet a similar fit as Model 2 ($\chi^2[1] = 1.7$, $p = .20$). Models 2 and 4 were identical in their deviances and information criteria. Given that variance between cycles was insignificant, we argue that Models 2 and 4 could serve as baseline models—these models demonstrated substantial between-country variation (see also Figure 4a). Depending on assumptions concerning correlated effects, meta-analysts may choose either model for further analyses.

Moderation by TIMSS cycle. The extent to which BFLPE may vary over time can be evaluated in several ways. In this section, we describe three possible approaches. First, the nesting of effect sizes in cycles can be modelled by introducing the TIMSS cycle as an *analytic level* in multilevel meta-analysis. Models 3 and 5 are example models that can quantify the

between-cycle variation directly. In our illustration, these two models did not indicate significant variation between cycles (see Table 6).

Second, meta-analysts can control for between-cycle BFLPE variation by introducing the TIMSS cycle as a *predictor variable*. For instance, Model 2 can be extended directly to a mixed-effects meta-regression model incorporating TIMSS cycles as a predictor variable as follows:

```
MEM3L.cycle <- rma.mv(effect_size ~ 1 + factor(year), var,
                      random=list(~1|country/ESID), data=bflpedat, method="REML")
```

This model did not uncover between-cycle differences in BFLPE ($Q_M[4] = 7.7, p = .10$), but only a tendency for the effect size for TIMSS 2011 to be slightly lower than the others. Alternatively, the TIMSS cycle identifier (`year`) can also be transformed into a `time` variable with codes 0, 1, 2, 3, and 4 as respective cycles with equidistant time differences, then inserted as a predictor variable. Like the previous model, this model resulted in an insignificant moderator test statistic ($Q_M[1] = 3.0, p = .08$) and a regression coefficient that indicated a small decrease in BFLPE over time, $B = 0.009$, 95% CI [-0.005, 0.023].

Third, the TIMSS cycle may be treated as a *grouping variable* in a subgroup meta-analytic approach, in which heterogeneities across countries can be cycle-specific, rather than homogeneous, across cycles. Recently, Pustejovsky et al. (2021) proposed a subgroup correlated-effects model that can be implemented with the assumption of $\rho = 0.5$ as follows:

```
V_mats <- impute_covariance_matrix(bflpedat$var, cluster =
                                   bflpedat$country, r = 0.5, smooth_vi = TRUE, subgroup =
                                   bflpedat$year)

REM3Ls <- rma.mv(effect_size, V = V_mats, random = list(~
               as.factor(year) | country), struct = "DIAG", data =
               bflpedat, method = "REML")
```

As in Model 4, the first step towards estimating this subgroup model is to create a sampling covariance matrix (`V_mats`) with the grouping in cycles included (`subgroup = bflpedat$year`). Along with effect sizes, this covariance matrix then is submitted to the `rma.mv` function with random effects that allow for cycle-specific variation within and between countries. This model resulted in an overall BFLPE of $\hat{\mu} = -0.457$ (95% CI [-0.494, -0.419]) and between-heterogeneity estimates of $\sigma_C^2 = 0.027$ (TIMSS 2003), $\sigma_C^2 = 0.032$ (TIMSS 2007), $\sigma_C^2 = 0.023$ (TIMSS 2011), $\sigma_C^2 = 0.029$ (TIMSS 2015), and $\sigma_C^2 = 0.016$ (TIMSS 2019). However, this model did not consider possible differences in the within-country heterogeneity estimates. Notably, other meta-analytic models are available to handle time dependencies, such as multivariate random-effects models with autoregressive structures of random effects (see Trikalinos & Olkin, 2012).

Moderation by cultural dimensions and economic development. We also tested the possible moderator effects from (a) cycle-invariant and country-specific indices of Hofstede's six cultural dimensions, and (b) cycle-specific and country-specific HDI. First, we extended Model 2 to three-level mixed-effects meta-regression models with each of these predictors (Models 2a and 2b; see Table 7). The respective R code for these models read:

```
MEM3L.culture <- rma.mv(effect_size ~ 1 + pdi + idv + mas + uai +
  lto + ivr, var, random=list(~ 1|country/ESID),
  data=bflpedat, method="REML")

MEM3L.hdi <- rma.mv(effect_size ~ 1 + HDI, var,
  random=list(~1|country/ESID), data=bflpedat, method="REML")
```

These models demonstrated significant moderator effects with smaller negative effects for countries with high economic development, yet no moderator effects from cultural dimensions.

The economic development index was the only variable explaining between-country

heterogeneity in BFLPE ($R_C^2 = 12.3\%$). Using Model 4 as the baseline model elicited the same conclusions, but with slightly smaller variance explanations (Models 4a and 4b; see Table 7).

Sensitivity analyses. As part of our analyses, we examined the extent to which meta-analytic findings were sensitive to influential effect sizes and the choice of our baseline model. We identified four influential effect sizes. Our inspection of the Baujat plot showed that some effect sizes contributed substantially to the overall heterogeneity (see Figure 4b). The graphical display of study heterogeneity (i.e., Gosh plot) showed a roughly symmetric and unimodal distribution of the effect sizes as a function of heterogeneity and suggested that subclusters of effect sizes due to possible outliers or influential effect sizes may not exist (see Figure 4c).

We also compared the weighted average effect sizes and indices between the five models presented in Table 6. Furthermore, we varied the choice of the within-study correlation ρ in Model 4 and observed that higher correlations were associated with larger between-study heterogeneity (see Supplementary Material 1). Finally, introducing a constant sampling correlation ρ to the three-level mixed-effects meta-regression models impacted the magnitude of the moderation effect of HDI and the variance explanations (see Table 7). To sum up, the results suggested the presence of influential effect sizes and the sensitivity of the meta-analytic findings to the choice of baseline model and assumptions on the correlated effects.

Step 6: Reporting and Documentation

The final step in synthesizing findings from complex survey data concerns the reporting and communication of meta-analytic findings. Meta-analyses are an essential source of information for education practitioners, policymakers, and decision-makers. Therefore, a meta-analysis should provide a clear description of the methodology used and enough information to reproduce the results, interpret the findings for multiple audiences, discuss how they relate to

previous literature, and report any study limitations (Pigott & Polanin, 2020). To present these elements, meta-analysts can draw from existing reporting guidelines, such as Quantitative Meta-Analysis Article Reporting Standards (Appelbaum et al., 2018). Publishing the analytic code, reports, and meta-analytic data can facilitate the replicability and transparency of the research process and findings (Moreau & Gamble, 2022).

Illustrative Example 2: Combining IPD from Complex Surveys and AD

Purpose of the Example

With our second example, we illustrate the capabilities of two-stage IPD meta-analysis to synthesize aggregated data (e.g., reported means, standard deviations, or correlations) and IPD from one or multiple complex sampling surveys in one meta-analysis. In stage 1, the effect sizes of interest and their sampling variances are extracted from the AD and generated from the IPD while accounting for the complex sampling design. To ensure comparability, the effect sizes generated from IPD must mimic those extracted from AD, and vice versa. In stage 2, these effect sizes are then pooled and examined for possible heterogeneity, moderation, selection or publication bias. Meta-analysts can examine whether the meta-analytic results differ across the two data sources and thus explore if both may lead to similar or substantively different conclusions (Cooper & Patall, 2009; V. Smith et al., 2011). The combination of IPD from complex sampling surveys and additional AD allows for testing different sampling designs and features (e.g., multi-stage cluster sampling vs. convenience sampling) for their moderator effects (e.g., Scherer et al., 2021). We argue that combining AD from published literature and IPD from complex sampling surveys represents a unique feature of the two-stage meta-analytic approach.

Step 1: Problem Formulation and Framing of the Meta-Analysis

This example is concerned with gender differences in secondary-school students' digital skills, that is, so-called "digital gender divides" (e.g., Van Dijk, 2020). Quantifying and explaining gender differences have become key activities in psychological research to understand the nature of psychological constructs, examine test fairness, or investigate indicators of equality (e.g., Eagly & Revelle, 2022; Else-Quest et al., 2010). The meta-analysis we illustrate was first published by Siddiq & Scherer, (2019), updated by Scherer et al., (2021), and highlights possible gender divides in digital contexts. Specifically, it addressed the following research questions:

- RQ1. To what extent do girls and boys in secondary education differ in their digital skills? (Pooled effect size)*
- RQ2. To what extent do digital gender divides vary across student samples, primary studies, and countries? (Heterogeneity)*
- RQ3. To what extent do characteristics of the study design, measurement, sampling, and countries explain heterogeneity in effect sizes? (Moderators)*

In the context of this meta-analysis, gender was indicated by the identified sex, and digital skills were broadly defined as the knowledge and skills students need to become digitally literate, such as digital information literacy, problem solving, and operational skills (e.g., Fraillon et al., 2019). Siddiq and Scherer (2019) included empirical studies of K-12 student samples with performance assessments of digital skills and quantitative reports of gender differences. This meta-analysis was not preregistered.

Step 2: Data Search and Selection

The authors searched for relevant publications in literature databases (e.g., PsycINFO, ERIC, ProQuest) and the IEA and OECD data repositories (e.g., ILSA Gateway, <https://ilsa-gateway.org/>). These database searches and the screening resulted in 24 publications, two of which provided IPD via the IEA data repository. Specifically, the IPD of the two IEA international large-scale assessments ICILS (International Computer and Information Literacy Study) 2013 and 2018 were available. In our example, we focus on samples of students in secondary education and use the updated, meta-analytic data set presented by Scherer et al. (2021). This dataset contained 21 publications and primary studies, 53 independent effect sizes, and student samples from 30 countries. Of the 21 primary studies, 19 provided aggregated data, and two provided IPD (i.e., ICILS 2013 and ICILS 2018). Overall, the meta-analytic data were based on $N = 137895$ students ($n_{\text{Girls}} = 67639$, $n_{\text{Boys}} = 70256$). For more details about the search and screening procedures, please review the original publications of this meta-analysis.

Step 3: Data Preparation

After retrieving the IPD from ICILS 2013 and 2018, we extracted the relevant variables to estimate the standardized mean differences and account for the complex survey design. Only ten of 105981 students in ICILS 2013 and 2018 did not provide information on gender and were thus excluded. Gender was coded as 1 (*girl*) and 0 (*boy*). To indicate digital skills, we used the set of five plausible values of the Computer and Information Literacy (CIL) construct (PV1CIL-PV5CIL). The core features of the complex sampling design were stored in several variables, such as students' final weights (TOTWGTS), jackknife replication codes (JKREPS), jackknife zones (JKZONES), and jackknife replication weights (SRWGT1-SRWGT75). For each student,

a unique student (IDSTUD) and school identifier (IDSCHOOL) were available. The country structure was indicated by the countries' ISO codes (IDCOUNTRY).

The meta-analytic data set contained the overall effect sizes (Hedges' g) and their sampling variances (v_g), and the complex structure of these data was indicated by identifiers of the independent and unique samples (IDSAMPLE), countries (IDCOUNTRY), and primary studies (IDSTUDY). Moreover, the data set contained several characteristics of the samples (e.g., sample sizes N , n_{Girls} , n_{Boys}), the primary studies (e.g., randomized vs. convenience sampling, publication year), the assessment of digital skills (e.g., interactive vs. static tasks, applied skills vs. knowledge, assessment of test fairness), and the countries (e.g., Gross Domestic Product [GDP], Hofstede's Power Distance Index [PDI]). Please find the data set with a detailed description of the variables in the online material.

Step 4: Analysis of IPD and Estimation of Effect Sizes

In the AD, estimates of the standardized mean differences were computed from the reported summary statistics, that is, the means ($\bar{X}_G$, $\bar{X}_B$), standard deviations (SD_G , SD_B), and sample sizes (n_G , n_B) of the female (G) and male (B) sub-samples. Following Borenstein et al.'s (2009) formulas, Hedges' g and its sampling variance v_g was computed from Cohen's d and its sampling variance v_d as follows:

$$d = \frac{\bar{X}_G - \bar{X}_B}{\sqrt{\frac{(n_G-1)SD_G^2 + (n_B-1)SD_B^2}{n_G+n_B-2}}} \quad \text{with } v_d = \frac{n_G+n_B}{n_G n_B} + \frac{d^2}{2(n_G+n_B)}$$

$$g = \left(1 - \frac{3}{4(n_G+n_B-2)-1}\right) \cdot d \quad \text{with } v_g = \left(1 - \frac{3}{4(n_G+n_B-2)-1}\right)^2 \cdot v_d$$

In some instances, these effect sizes could only be retrieved from reported test statistics, such as t or F values (see Siddiq & Scherer, 2019). If a study provides AD from a complex survey, and the means and standard deviations are not adjusted accordingly, some corrections of the effect sizes

are possible. For instance, Hedges (2007) developed standardized mean differences that directly incorporate information about clustered data structures (e.g., intraclass correlations and cluster sizes).

In the IPD, we ran country-specific, multi-group models (`GROUPING IS GIRL (0=Boys 1=Girls)`) that estimated the means (`[PVCIL];`) and variances (`PVCIL;`) for the female and male sub-samples within each country in the software *Mplus*. These models incorporated students' total weights (`WEIGHT = TOTWGTS`), were run for each of the five plausible-value data sets, and were then combined via Rubin's rules (`TYPE = IMPUTATION`). We further chose robust maximum-likelihood estimation (`ESTIMATOR = MLR`) with the clustering of the data in jackknife replicates (`CLUSTER = JKREPS`) and stratification by jackknife zones (`STRATIFICATION = JKZONES`). This analytic setup represents the core features of the complex sampling design of ICILS (Mikheeva & Meyer, 2020). We used the estimates of the model-based means and standard deviations to compute Hedges' g and its sampling variance v_g with the above-described formulas.

Step 5: Meta-Analysis of the Effect Sizes

In the next step, we pooled the effect sizes (RQ1), quantified their heterogeneity (RQ2), and tested for moderator effects (RQ3).

Meta-analytic baseline model. In the meta-analytic data set, each sample provided only one effect size, multiple samples were included in most primary studies, and, in addition, some countries were represented by multiple samples (e.g., Chile participated in ICILS 2013 and 2018). This data structure indicated effect size multiplicity at the levels of studies and countries with hierarchical rather than correlated effects. Hence, to establish a meta-analytic baseline model for the entire data set comprising AD and IPD, we estimated and compared several

multilevel random-effects models (see Supplementary Material 2): A three-level random-effects model with effect sizes nested in studies (Model REM3) represented the data better than a model ignoring the nesting ($\chi^2[1] = 7.7, p = .006$) and indicated significant variation within studies ($\sigma_W^2 = 0.013, 95\% \text{ CI } [0.008, 0.023]$) and between studies ($\sigma_B^2 = 0.021, 95\% \text{ CI } [0.003, 0.067]$).

Extending this model to a cross-classified random-effects model (Model CCREM4) with an additional nesting of effect sizes in countries did not improve the model fit ($\chi^2[1] = 2.3, p = .13$), yet reduced the variation within studies ($\sigma_W^2 = 0.003, 95\% \text{ CI } [0.000, 0.019]$) and increased the between-country variance ($\sigma_C^2 = 0.009, 95\% \text{ CI } [0.000, 0.020]$). While this result suggested that some variation is located between countries, the three-level random-effects model represented a more parsimonious model than the cross-classified model and was thus accepted as a meta-analytic baseline model. The resultant, pooled effect size was $\bar{g} = 0.106$ (95% CI [0.020, 0.192]) in favor of girls, and the overall heterogeneity was large, $I^2 = 95.7\%$.

For synthesizing only the AD, a standard random-effects model was sufficient and indicated an insignificant, pooled effect size of $\bar{g}_{AD} = 0.081$ (95% CI [-0.021, 0.184]) with $I_{AD}^2 = 94.3\%$. For synthesizing only the IPD, a three-level random-effects model described the nesting of effect sizes in countries. This model resulted in a larger pooled effect size than the estimate for only the AD, $\bar{g}_{IPD} = 0.218$ (95% CI [0.174, 0.262]) with $I_{IPD}^2 = 90.2\%$. Figure 5 summarizes the AD-only and IPD-only effect sizes in forest plots.

Moderator analyses. A mixed-effects meta-regression with task interactivity, type of sampling, test fairness, PDI, and GDP revealed a positive effect of GDP ($B = 0.097, 95\% \text{ CI } [0.027, 0.167]$), explaining about 16.6% of the within-study and 26.4% of the between-study variation. Another model included the assessment of applied skills and its interaction with the PDI (specified as `AppliedSkills*scale(PDI)`) as moderators. Despite significant main

effects, the interaction effect was insignificant ($B = 0.369$, 95% CI $[-0.034, 0.772]$), and the overall model explained about 2.7% and 8.2% of the within- and, respectively, between-study variation.

Selection bias and influential effect sizes. Countries participating in ICILS were not randomly selected but invited to participate, and AD from published papers might be prone to publication bias. As a consequence, we performed tests for selection and publication bias (see Supplementary Material 2). Except for the trim-and-fill analyses, which suggested that about 12 effect sizes (L_0^+) would be missing, all other tests did not provide any evidence for such bias. Moreover, no effect size was marked as influential in the meta-analytic data set.

Sensitivity analyses. As part of our sensitivity analyses, we examined the extent to which the pooled effect sizes and amounts of residual heterogeneity differed between AD and IPD. When AD and IPD are meta-analyzed jointly, researchers may want to explore the differences and similarities between these types of data to, for instance, make visible publication bias, the effects of different data modeling approaches or study designs, or highlight the importance of open science practices, transparency, and data availability (e.g., Hedges & Schauer, 2019; Pigott & Polanin, 2020; Scherer et al., 2021). Given that IPD may not be available for all primary studies with complex survey designs, for instance, due to issues related to data protection or accessibility, availability bias may occur when IPD availability is associated with study quality or effects (Riley et al., 2021). Ideally, meta-analysts reach the same conclusions when analyzing AD and IPD.

Our separate meta-analyses of the AD and IPD already indicated that the pooled effect sizes were largely different. To further substantiate this observation and to test for differences in heterogeneity, we estimated and compared three meta-analytic models with varying assumptions

on the model parameters (see Table 8). These models were informed by Rubio-Aparicio et al.'s (2020) framework of mixed-effects meta-analytic models with categorical moderators. Given the multilevel nature of the meta-analytic data, we specified three-level mixed-effects meta-regression models (see Supplementary Material 2).

Model 1 assumed that estimates of the pooled effect size and heterogeneity between samples and between studies or countries were specific to AD and IPD. We implemented the data-specific nature of these estimates using the `rma.mv` function, including the binary variable IPD as a moderator (`mods=~IPD`), and allowing the random effects to vary between AD and IPD (e.g., `random=list(~IPD|IDSAMPLE,~IPD|IDCOUNTRY)`; see Table 8). For parsimony, Model 1 further assumes that the random effects are independent (`struct="DIAG"`). Model 1 with data-specific between-sample and between-country (residual) heterogeneity resulted in a positive and significant moderation effect of IPD ($B = 0.144$, 95% CI [0.032, 0.256]), suggesting that the pooled effect sizes differed significantly between AD and IPD, with larger effects for the latter. Between-sample variances were $\tau_{AD}^2 = 0.035$ (95% CI [0.011, 0.093]) and $\tau_{IPD}^2 = 0.003$ (95% CI [0.001, 0.013]), and between-country variances were $\gamma_{AD}^2 = 0.002$ (95% CI [0.000, 0.073]) and, respectively, $\gamma_{IPD}^2 = 0.009$ (95% CI [0.001, 0.020]).

Model 2 constrained the between-country or between-study residual heterogeneity to a single estimate (see Table 8). Comparing this model to Model 1 with constrained between-country heterogeneity suggested the preference of Model 2 (Likelihood-ratio test: $\chi^2[1] = 1.2$, $p = .27$, and smaller information criteria of Model 2). Extending Model 2 to Model 3 by constraining the between-sample residual heterogeneity to one estimate did not improve the model fit, $\chi^2(1) = 6.92$, $p = .009$. Model 2 had lower information criteria and was preferred over

Model 3. Notice that Models 1-3 can also be specified without IPD as a moderator to test the data specificity of the amounts of overall rather than residual heterogeneity.

These model comparisons suggested that pooled effect sizes and between-sample residual variances differed between AD and IPD. Given these differences, we may argue that the pooling of effect sizes and the quantification of (residual) heterogeneity were sensitive to the type of meta-analytic data in our illustrative example. One may therefore question whether combining AD and IPD in one meta-analysis is reasonable.

Step 6: Reporting and Documentation

As noted in our first example, the reporting of the meta-analytic process and results may follow the Quantitative Meta-Analysis Article Reporting Standards. Making available the search protocols, a list of primary studies (including effect sizes, sampling variances, and coded variables), the meta-analytic data set, and the analytic code could further support the replicability and transparency of the meta-analysis.

General Discussion

This paper illustrated how two-stage IPD meta-analysis can be utilized to synthesize data from complex sampling surveys. After reviewing current analytic approaches to synthesizing IPD with hierarchical structures, we explained the data complexities related to complex sampling surveys and discussed their implications for data analysis and synthesis. One of the main goals of this paper was to showcase the potential of two-stage IPD meta-analysis for dealing with complex sampling design features in primary data and dependencies among effect sizes in meta-analytic data. We illustrated this potential with an example from educational psychology and proposed a sequence of steps and a methodological toolbox to meta-analyze IPD from complex surveys (see Table 1). Up to date, it was unclear how to incorporate IPD collected from

probability samples (Hussong et al., 2013). The two-stage approach offers the possibility to include these data in the synthesis of research evidence.

Implications for Meta-Analysis of IPD From Complex Sampling Surveys

Generally, we consider two-stage IPD meta-analysis to be useful for synthesizing IPD from complex sampling surveys in many ways: First, two-stage IPD meta-analysis enables researchers to account for study-specific sampling procedures, clustering, stratification, and survey weights from two or more complex surveys. In contrast, one-stage IPD meta-analysis cannot incorporate different sample design features across all studies. The two-stage approach provides a more flexible approach to accommodate for differences in these survey features.

Second, the analysis of raw data in a two-stage IPD meta-analysis enables researchers to standardize analyses across studies and directly derive the effect sizes of interest (Cooper & Patall, 2009). Critics of AD meta-analyses point to the risk of drawing conclusions that may be subject to aggregation biases and depend heavily on the quality of published results (Sharpe, 1997). Moreover, reported effect sizes can have different meanings across studies and may be derived from different analytic models. These differences compromise their comparability and, ultimately, the validity of any inference drawn from meta-analytic findings (Nugent, 2017). In two-stage IPD meta-analysis, meta-analysts are in control of the analytic approaches and may test the comparability of the measures across studies, analytic levels, subgroups within the samples, or study designs. Thus, two-stage IPD meta-analysis has the potential to reduce biases due to measurement error and aggregation.

Third, the flexibility of a two-stage IPD meta-analysis extends the range of model parameters and effect sizes available for subsequent meta-analyses. These parameters may be derived from model- or design-based approaches to, for instance, multiple linear regression

(Becker & Wu, 2007), multilevel modeling (Lorah, 2018), and structural equation modeling (Cheung & Chan, 2005). Given this flexibility, not only model-inherent, but also model-derived parameters become accessible meta-analytically, including moderation and mediation effects, factor loadings, contextual effects, and cross-level interactions (Pigott et al., 2012; Scherer & Teo, 2020). Since an SEM approach is used to conduct the stage-one analysis, it can effectively handle complex data structures, non-normal data, and missing data in a unified framework. Some SEM packages, e.g., *Mplus*, can calculate effect sizes that are functions of the parameters. The sampling covariance matrices of the effect sizes can also be automatically calculated with a multivariate delta method. Researchers may avoid the tedious calculations in deriving the effect sizes and their sampling covariance matrices. Unlike the one-stage approach, the two-stage approach offers possibilities to derive such complex parameters *and* quantify their model-based sampling variation (Cheung & Cheung, 2016). Thus, we argue that the two-stage IPD meta-analysis flexibly accommodates complex statistical analyses that are not feasible when only aggregated data are available.

Finally, a two-stage IPD meta-analysis can handle the statistical dependencies that can arise when combining multiple effect sizes derived from complex surveys. As noted earlier, complex survey designs impact both primary *and* meta-analytic data structures. In Stage 2, a two-stage IPD meta-analysis allows researchers to examine different meta-analytic models to handle effect size multiplicity (Cheung, 2019; López-López et al., 2018; Pustejovsky & Tipton, 2021). The meta-analytic models presented in this study allow researchers to pool weighted mean effect size estimates from meta-analytic datasets containing information from multiple survey cycles, multiple complex surveys, or AD and IPD effect sizes. In addition, researchers

can use the models to understand sources of heterogeneity in the data and examine whether these sources are associated with moderators that may operate at different analytic levels.

Limitations and Future Research Directions

Although the two-stage IPD meta-analytic approach has many attractive features for synthesizing complex survey data, it still has several limitations that warrant further investigation.

Sampling heterogeneity. Between-sample heterogeneity across strata and studies is a significant threat to the internal validity of a two-stage IPD meta-analysis. Combining IPD from different sampling designs in a two-stage IPD meta-analysis can lead to misidentification of effects as theoretically significant when these effects result from sampling composition differences that were not modeled adequately (Hussong et al., 2013). In a two-stage approach, it is therefore important to consider these differences, for instance, by examining possible moderator effects of the sampling designs.

Measurement heterogeneity. Another issue in two-stage IPD meta-analysis is related to measurement heterogeneity. The pooling of IPD from multiple complex surveys utilizing the same measures raises the issue of measurement equivalence across surveys (see Hussong et al., 2013). While measurement harmonization procedures can determine or establish some level of equivalence, for instance, via measurement invariance testing, full equivalence hardly will be achieved across many surveys or samples (Kim et al., 2017). Establishing the conceptual comparability of measures is imperative, and, whenever possible, statistical comparability should be tested. We argue that additional research is needed to combine approaches to measurement invariance with many groups and IPD meta-analyses when the same measures are administered across data sets. However, when different measures are administered across data sets, invariance

testing is not applicable, and researchers can only rely on the conceptual comparability of measures. In this situation, examining the possible moderator effects by the types and features of the measures can shed light on the impact of measurement heterogeneity on the effect sizes of interest.

Selection bias. Different types of selection bias may influence IPD meta-analysis with complex sampling survey data (Ahmed et al., 2012): First, researchers using complex survey data do not control primary sampling units. Complex surveys often include countries or geographical areas that participate voluntarily or self-select into these surveys depending on the outcome of interest. Thus, resultant effect size estimates can hardly be generalized to countries or geographical areas (Heckman, 1990). Second, publication bias may be apparent, for instance, when national or international institutions decide not to release IPD. As noted earlier, this may cause availability bias especially when combining IPD with AD. These forms of selection bias hardly can be controlled; yet we encourage meta-analysts to make an effort to characterize sampling procedures involved in IPD and to examine any possible influence from selection bias on their results.

Time and complexity. Conducting two-stage IPD meta-analyses is time-consuming and complex. Unlike AD meta-analysis, meta-analysts need to extract and prepare IPD and generate relevant effect size estimates. As we described in the Stage 1 analyses, generating such estimates from complex survey IPD requires several analytic steps and often complex statistical models. Thus, meta-analysts need to weigh the benefits of meta-analyzing IPD from complex surveys against these demands.

Conclusions

Two-stage IPD meta-analysis offers a flexible approach to analyzing and synthesizing research evidence from complex sampling surveys. In this paper, we argue that the potential that lies in this approach can be utilized to test new hypotheses and their consistency across multiple study designs, samples, and measurements. The approach offers several advantages over single-study analysis and AD meta-analysis: First, it allows researchers to incorporate the complex features of the data into the analysis *and* synthesis. Second, two-stage IPD meta-analysis allows for testing the comparability of the measures across analytic levels or groups. Third, researchers can use a wide range of statistical methods to derive effect sizes of interest and their sampling variances directly. Importantly, all of these techniques are well integrated into the SEM framework. Researchers can thus address all of these questions within the same model. Finally, the approach can disaggregate different levels to examine various heterogeneity sources and test whether study, sample, or measurement characteristics are related to this heterogeneity. When choosing two-stage IPD meta-analysis, researchers should consider the nature of the primary data (e.g., clustered data, sampling weights, stratification), the types of effects of interest (e.g., contextual effects from multilevel data), and reflect on how the structure of the primary data may affect the structure of the meta-analytic data (e.g., effect size multiplicity). The two-stage meta-analytic approach has the potential to synthesize IPD sets from multiple complex surveys and survey cycles. Moreover, the broad range of stage-2 meta-analytic models also allow meta-analysts to combine and compare AD and IPD. Given this potential, we believe that two-stage IPD meta-analysis can help create a cumulative body of knowledge in the social sciences.

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Tables

Table 1*Step-by-Step Guide of the Two-Stage IPD Meta-Analysis of Complex Survey Data*

Step	Description
Step 1: Problem formulation and framing of the meta-analysis	<ul style="list-style-type: none"> ▪ Definition of the research questions and objectives ▪ Development of the operational definitions of the constructs and variables of interest, the sample, study context, and the effects ▪ Definition of inclusion and exclusion criteria ▪ Delineation of the sources and procedures to find relevant evidence (search strategy) ▪ Pre-registration of the meta-analysis (e.g., via OSF)
Step 2: Data search and selection	<ul style="list-style-type: none"> ▪ Identification of the relevant IPD ▪ Screening following inclusion and exclusion criteria ▪ Selection of the eligible IPD ▪ Extraction of the IPD from data repositories, publications, and other sources (e.g., contacting authors, national data services) ▪ Documentation of the search, screening, and extraction (e.g., PRISMA flowchart for IPD meta-analysis)
Step 3: Data preparation	<ul style="list-style-type: none"> ▪ Selection of the variables to represent the constructs of interest (e.g., item responses vs. scale scores) ▪ Selection of the features representing the complex data structure in the data analysis (e.g., sampling weights, cluster identifiers) ▪ Data cleaning, coding, and preparation for the stage-1 analyses (e.g., coding of variables, scaling of weights, sub-setting) ▪ Coding of possible moderator variables (e.g., sample, study, and measurement characteristics)
Step 4: Analysis of IPD and estimation of effect sizes	<ul style="list-style-type: none"> ▪ Analysis of the IPD, accounting for the complex survey features (e.g., multilevel modeling with sampling weights), handling missing data (e.g., multiple imputation), and including possible tests for comparability across clusters or groups (e.g., invariance testing) ▪ Estimation of the effect sizes of interest and the respective sampling (co-)variances
Step 5: Meta-analysis of the effect sizes	<ul style="list-style-type: none"> ▪ Identification of a meta-analytic baseline model to represent the structure of the meta-analytic data (i.e., correlated, hierarchical, or subgroup structures) and to handle effect size multiplicity (e.g., robust variance estimation, multilevel or multivariate meta-analysis) ▪ Meta-analytic synthesis of the effect sizes and sampling variances ▪ Quantifying heterogeneity among the effect sizes ▪ Investigation of possible selection bias and influential effect sizes ▪ Moderator analyses (e.g., meta-regression, subgroup analysis) ▪ Sensitivity analyses and robustness checks
Step 6: Reporting and documentation	<ul style="list-style-type: none"> ▪ Interpretation and communication of the meta-analytic findings ▪ Open-access publication of reports, analytic code, and data

Table 2*Structure of the Primary IPD Including the First Plausible Value of Mathematics Achievement (Stage 1)*

Year	Country	Class ID	Student ID	ASBM03A	ASBM03B	ASBM03C	ASBM03D	ASMMAT 01	Student Weight	Classroom Weight
2003	AUS	1	1	3	1	4	3	421.83	0.99	5.55
2003	AUS	1	2	2	1	2	2	593.06	0.99	5.55
2003	AUS	2	3	2	3	2	2	531.41	0.99	6.36
2003	...	...	...	...	...	...	...	...	...	...
2003	SGP	501	10000	3	3	2	4	716.83	1.02	2.99
2003	SGP	502	10001	4	3	4	2	662.88	1.02	11
2003	SGP	503	10002	2	1	2	2	533.68	1.03	3.99
2003	...	...	...	...	...	...	...	...	...	...
2007	AUS	1001	20001	3	3	1	2	471.69	1.26	12.96
2007	AUS	1002	20002	3	2	2	4	413.21	1.45	26.82
2007	...	...	...	...	...	...	...	...	...	...
2007	SVK	2001	40001	3	2	2	2	507.45	1.09	6.42
...	...	...	...	...	...	...	...	...	...	...

Note. ID = Identifier. ASBM03A-D represent the students' responses to the four self-concept items. ASMMAT01 represents the first plausible value of mathematics achievement.

Table 3*Fit Statistics of the Multi-Group Multilevel Measurement Invariance Models*

Model	RMSEA	CFI	SRMR-W	SRMR-B	$\Delta\chi^2(\Delta df)$
TIMSS 2003					
Configural model	.000	.998	.00	.04	
L1 invariance model	.077	.947	.04	.08	2829.83 (113)*
L2 invariance model	.048	.959	.04	.14	241.21 (113)*
L1 and L2 invariance model	.047	.958	.04	.12	72.18 (14)*
Contextual model	.053	.931	.04	.14	
TIMSS 2007					
Configural model	.000	.995	.00	.04	
L1 invariance model	.066	.956	.03	.06	3009.02 (173)*
L2 invariance model	.040	.969	.03	.10	281.92 (173)*
L1 and L2 invariance model	.039	.969	.03	.10	13.09 (16)
Contextual model	.051	.934	.03	.12	
TIMSS 2011					
Configural model	.000	.996	.00	.02	
L1 invariance model	.061	.968	.02	.07	3809.21 (217)*
L2 invariance model	.037	.977	.02	.11	320.37 (217)*
L1 and L2 invariance model	.036	.977	.02	.11	51.87 (19)*
Contextual model	.056	.927	.03	.14	
TIMSS 2015					
Configural model	.027	1.000	.00	.07	
L1 invariance model	.063	.963	.02	.10	8912.34 (221)*
L2 invariance model	.036	.976	.02	.10	189.29 (221)
L1 and L2 invariance model	.036	.975	.02	.11	35.76 (24)
Contextual model	.061	.910	.04	.14	
TIMSS 2019					
Configural model	.027	1.000	.00	.01	
L1 invariance model	.067	.962	.03	.08	10811.13 (253)*
L2 invariance model	.040	.973	.03	.09	354.16 (253)*
L1 and L2 invariance model	.039	.973	.03	.09	22.06 (29)
Contextual model	.057	.924	.03	.11	

Note. Configural model: a model with one factor for mathematics self-concept and factor loadings allowed to vary across levels and countries. L1 invariance model: factor loadings restricted to be invariant across countries at L1. L2 invariance model: factor loadings are restricted to be invariant across countries at L1 and L2, but with factor loadings allowed to vary across levels. L1 and L2 Invariance Model: a model with factor loadings restricted to be invariant across countries and levels. L1 = Level 1 (student level), L2 = Level 2 (classroom level).

* $p < .001$

Table 4*Structure of the Meta-Analytic Data (Stage 2)*

ESID	Year	Country	N	BFLPE	var	PDI	IDV	MAS	UAI	LTO	IVR	HDI
1	2003	AUS	4225	-0.60	0.009	38	90	61	51	21	71	0.91
2	2003	BFL	4668	-0.45	0.003	65	75	54	94	82	57	0.89
3	2003	COT	4284	-0.27	0.003	39	80	52	48	36	68	0.88
...	...	...	...	...	...	...	...	...	...	...	...	...
200	2019	AAD	8621	-0.62	0.007	80	38	53	68	23	34	0.89
201	2019	ADU	7251	-0.44	0.003	80	38	53	68	23	34	0.89
202	2019	ARE	25173	-0.62	0.002	80	38	53	68	23	34	0.89
203	2019	AUS	5764	-0.49	0.003	38	90	61	51	21	71	0.94
204	2019	AUT	4420	-0.45	0.003	11	55	79	70	60	62	0.92
...	...	...	...	...	...	...	...	...	...	...	...	...

Note. ESID = Effect size identifier, BFLPE = standardized Big-Fish-Little-Pond-Effect size (Marsh et al., 2009), *var* = Sampling variance, PDI = Power Distance Index, IDV = Individualism vs. collectivism, MAS = Masculinity vs. femininity, UAI = Uncertainty Avoidance Index, LTO = Long-term vs. short-term orientation, IVR = Indulgence vs. restraint, HDI = Human Development Index. Countries are coded by the ISO-3 letter codes. The year refers to the respective TIMSS cycle.

Table 5*Specification of Meta-Analytic Baseline Models in the R Package metafor*

Model	Specification in metafor
Model 1: Standard random-effects model	<code>rma.mv(effect_size, var, random=list(~1 ESID), data=bflpedat, method="REML")</code>
Model 2: Three-level random-effects model with effect sizes nested in countries	<code>rma.mv(effect_size, var, random=list(~1 country/ESID), data=bflpedat, method="REML")</code>
Model 3: Three-level random-effects model with effect sizes nested in TIMSS cycles	<code>rma.mv(effect_size, var, random=list(~1 year/ESID), data=bflpedat, method="REML")</code>
Model 4: Three-level random-effects model with effect sizes nested in countries and a constant sampling correlation ($\rho = 0.5$)	<code>V_mat <- impute_covariance_matrix(bflpedat\$var, cluster=bflpedat\$country, r=0.5, smooth_vi=TRUE) rma.mv(effect_size, V=V_mat, random=list(~1 country/ESID), data=bflpedat, method="REML")</code>
Model 5: Four-level cross-classified random-effects model	<code>rma.mv(effect_size, var, random=list(~1 country/ESID, ~1 year), data=bflpedat, method="REML")</code>

Table 6*Weighted Average Effect Sizes and Heterogeneity of the BFLPE*

Baseline model	$\hat{\mu}$ [95 % CI]	σ_{ES}^2 [95 % CI]	σ_C^2 [95 % CI]	σ_Y^2 [95 % CI]	I_{ES}^2	I_C^2	I_Y^2
Model 1: Standard random-effects model	-.458 [-.481, -.436]	.025 [.020, .030]	-	-	82.4%	-	-
Model 2: Three-level random-effects model with effect sizes nested in countries	-.451 [-.486, -.416]	.004 [.002, .006]	.021 [.014, .031]	-	12.1%	70.0%	-
Model 3: Three-level random-effects model with effect sizes nested in TIMSS cycles	-.458 [-.484, -.432]	.025 [.020, .031]	-	.000 [.000, .002]	82.4%	-	0.0%
Model 4: Three-level random-effects model with effect sizes nested in countries and a constant sampling correlation ($\rho = 0.5$)	-.456 [-.490, -.421]	.007 [.005, .010]	.016 [.010, .026]	-	24.7%	57.0%	-
Model 5: Four-level cross-classified random-effects model	-.452 [-.489, -.415]	.003 [.001, .006]	.021 [.014, .031]	.000 [.000, .002]	10.9 %	70.6%	0.7%

Note. $\hat{\mu}$ = Weighted average effect size of the BFLPE, σ_{ES}^2 = Variation between effect sizes within the respective hierarchical cluster, σ_C^2 = Between-country variation, σ_Y^2 = Between-cycle variation. I_{ES}^2 , I_C^2 , and I_Y^2 are the corresponding heterogeneity indices. The 95% confidence intervals of $\hat{\mu}$ in Models 1-4 are cluster-robust and resulted from a bias-reduced linearization (Pustejovsky, 2021).

Table 7*Moderator Effects of the Cultural and Economic Indicators*

Moderator	Three-level mixed-effects meta-regression				Three-level mixed-effects meta-regression with a constant sampling correlation ($\rho = 0.5$)			
	Model 2a		Model 2b		Model 4a		Model 4b	
	<i>B</i>	<i>SE</i>	<i>B</i>	<i>SE</i>	<i>B</i>	<i>SE</i>	<i>B</i>	<i>SE</i>
Intercept	-0.137	0.174	-0.812	0.225	-0.166	0.177	-0.931	0.158
<i>Cultural dimensions</i>								
PDI	-0.002	0.002	-	-	-0.002	0.002	-	-
IDV	-0.002	0.001	-	-	-0.002	0.001	-	-
MAS	-0.001	0.001	-	-	-0.001	0.001	-	-
UAI	-0.001	0.001	-	-	-0.001	0.001	-	-
LTO	0.000	0.001	-	-	0.001	0.001	-	-
IVR	0.000	0.002	-	-	0.001	0.002	-	-
<i>Economic development</i>			-	-				
HDI	-	-	0.426*	0.258	-	-	0.559*	0.186
<i>Moderator test</i>								
$Q_M(df)$	8.6 (6), $p = .20$		5.5 (1), $p = .02$		8.9 (6), $p = .18$		9.1 (1), $p = .003$	
<i>Variance explanation</i>								
R_{ES}^2	0.0%		2.5%		0.0%		0.3%	
R_C^2	5.5%		12.3%		6.9%		11.6%	

Note. PDI = Power Distance Index, IDV = Individualism vs. collectivism, MAS = Masculinity vs. femininity, UAI = Uncertainty Avoidance Index, LTO = Long-term vs. short-term orientation, IVR = Indulgence vs. restraint, HDI = Human Development Index, df = Degrees of freedom, R_{ES}^2 = Proportional variance reduction at the level of effect sizes within countries, R_C^2 = Proportional variance reduction at the level of countries. In Models 2a and 4a, 42 effect sizes were excluded due to missing data in the cultural orientation indices. The 95% confidence intervals are cluster-robust and resulted from a bias-reduced linearization (Pustejovsky, 2021).

* $p < .05$

Table 8

Specification of the Meta-Analytic Models to Compare the Pooled Effect Sizes and their Residual Heterogeneity between AD and IPD

Model	Specification in metafor
Model 1: Data-specific effect sizes, data-specific between-country, and data-specific between-sample residual heterogeneity	<code>rma.mv(g, vg, random = list(~ IPD IDSAMPLE, ~ IPD IDCOUNTRY), method = "REML", data = dat, tdist = TRUE, test = "t", mods =~ IPD, struct = "DIAG")</code>
Model 2: Data-specific effect sizes, overall between-country heterogeneity, and data-specific between-sample residual heterogeneity	<code>rma.mv(g, vg, random = list(~ IPD IDSAMPLE, ~ 1 IDCOUNTRY), method = "REML", data = dat, tdist = TRUE, test = "t", mods =~ IPD, struct = "DIAG")</code>
Model 3: Data-specific effect sizes, overall between-country heterogeneity, and overall between-sample residual heterogeneity	<code>rma.mv(g, vg, random = list(~ IPD IDSAMPLE, ~ 1 IDCOUNTRY), method = "REML", data = dat, tdist = TRUE, test = "t", mods =~ IPD, struct = "ID")</code> <code>rma.mv(g, vg, random = list(~ 1 IDSAMPLE, ~ 1 IDCOUNTRY), method = "REML", data = dat, tdist = TRUE, test = "t", mods =~ IPD)</code>

Note. The variable IPD is coded as 1 (*IPD available*) and 0 (*only AD available*). “Data-specific” means that the parameters are estimated for each of the two data sources (i.e., AD and IPD). “Overall” means that only one estimate of the parameter is provided, without distinguishing between AD and IPD.

Figures

Figure 1*PRISMA Flowchart Representing the Selection Process of the IPD Meta-Analysis*

Note. IPD = Individual participant data, n = Number of primary studies, k = Number of publications (records).

Figure 2*Multilevel Latent Covariate Model to Estimate the BFLPE*

Note. W = Within (student) level, B = Between (classroom) level.

Figure 3*Meta-Analytic Data Structures Representing the Dependencies among the BFLPE Effect Sizes*

Note. Panel A shows the hierarchical nesting of multiple effect sizes in countries. Panel B shows the hierarchical nesting of multiple effect sizes in TIMSS cycles. Panel C shows the cross-classified nesting of multiple effect sizes in countries and TIMSS cycles.

Figure 4

Plots Characterizing the Meta-Analytic Data: (a) Forest Plot of Effect Sizes for Countries across TIMSS Cycles; (b) Baujat Plot; (c) Gosh Plot.

B

C

Note. Panel (a) indicates the participating countries by their ISO-3 letter codes. BFLPE = Big-Fish-Little-Pond-Effect.

Figure 5*Forest Plots of the Effect Sizes Describing Gender Differences in AD and IPD*

(a) Effect sizes from AD

(b) Effect sizes from IPD

Note. AD = Aggregated data, IPD = Individual participant data, RE = Random-effects model. Effect sizes represent Hedges' g as the standardized mean differences in digital skills between girls and boys.